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Abstract

We examine the role that insurance plays in mitigating the effect of climate events on bank loan outcomes in the context of agricultural finance. We find that the relationship between county-level deviations in crop yields to local banks' agricultural loans past due are larger after accounting for county-level crop indemnifications. We estimate that a one standard deviation increase in county-level crop indemnifications is associated with a decrease in agricultural loans past due by 6 basis points (bps), about one fifth of the time series variation in average agricultural loans past due. We then consider a climate scenario pathway from the Climate Impact Lab for possible future losses. Under a high emissions scenario, we find increases in agricultural loans past due of approximately 17 bps nationally if insurance coverage does not increase commensurately with increased risk. We argue that the implications of climate change on agricultural lending may be exacerbated by the practice of carryover debt, in which agricultural lenders may restructure short-term production loans under stress from poor production into longer term loans often backed by farmland.

Keywords: climate related financial risk, insurance, banking, agriculture, subsidies

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"Thank goodness we have federal crop insurance. It's nothing like making a crop, but it will keep the farmers in business."[1]

I. Introduction

Quantifying the effects of climate change on the financial system is an area of recent economic and financial interest, though there remain multiple challenges. There are uncertainties surrounding the paths of climate change, the associated damage functions of a specific weather event, accounting for the adaptations that economic and financial agents take in response to climate change, and incorporating the stability of structural assumptions underpinning the financial system in the context of climate change. Regarding structural assumptions, data limitations often restrict the ability of researchers to understand the role that insurance plays in insulating banks. Yet, the dependency of the financial system on insurance is believed to have important implications for the mitigation and amplification of climate related risks to asset prices and the financial system (Financial Stability Board (2020)).

In this paper, we study the role that insurance plays in mitigating the pass through of climate risks to financial institutions. Agricultural finance is a natural setting to study this question, as there exists substantial time-series and cross-sectional variation, and comparatively rich information on county-level insurance coverage. Furthermore, understanding the pass through of climate risks to agricultural finance and the role of insurance is relevant for forward looking risk management. For example, climate change is predicted to have large effects on maize and soybeans in temperate climates at latitudes encompassing the majority of agricultural producing regions in the United States (Jägermeyr et al. (2021)). Meanwhile, maize and soy represent 59 percent of all crops covered by the Federal Crop Insurance Program (FCIP) by value as of 2019 and more than 90 percent of planted acres for those crops were covered by FCIP (Congressional Research Service

[1] Cotton farmer in the Texas Panhandle during the 2020 drought quoted in "Drought Devastates U.S. Cotton Harvest; Farmers, particularly in Texas, are abandoning failed crops in droves, and cotton prices are rising." The Wall Street Journal Online, By Ryan Dezember. 16 August 2022.

(2021)).

We first examine the historical relationship between crop yields, crop insurance, and agricultural loan performance. We then use forward-looking predictions on yields and the estimated historical relationships between yields and loan outcomes to quantify the possible consequences of climate change on agricultural loan performance under alternative assumptions on future indemnifications.[2]

A growing body of research examines the relationship between climate change and financial risks, often bifurcating the discussion into physical risks and transition risks (Bolton et al. (2020)). Physical risks describe the economic costs and financial losses associated with increased frequency or severity of acute weather events, such as floods or hurricanes, and chronic indirect effects from climate changes, such as changes to soil conditions. Meanwhile, transition risks reference costs or losses associated with changes in policies, preferences, or technologies toward a low-carbon economy. In the context of climate-related financial risks, insurance and government subsidy programs are often thought to be important mitigants that have tempered the effects of past weather events on the loan performance of affected businesses or assets (see, Avtar et al. (2021), Anderlik et al. (2022)). At the same time, dependence on insurance and government subsidies may also be a source of risk to the extent that premiums adjust to reflect changing climate conditions or subsidies do not keep pace with the rate of extreme weather events. Accounting for insurance in estimating the transmission of climate events on financial outcomes is therefore important in both quantifying the effects of the climate, and understanding the dependencies of creditors on insurance upon which continued insulation from climate risks may rely.

We show that agricultural past due loans in the United States have a statistically significant, but modest relationship with county-level crop production. A county experiencing a one standard deviation decrease in crop production relative to its own historical norms is associated with a 9 bps increase in past due rates, relative to a mean past due rate of 73 bps. However, we find that the

[2]Indemnification is compensation for the loss or damage suffered by a party to an indemnity agreement. In the context of crop insurance, the insurer compensates an insured farmer for the damages or losses incurred during a hazard event, in return for premiums paid by the farmer.

effect is about fifty percent larger (13 bps) after accounting for crop indemnifications per policy in the county, consistent with the view that insurance programs blunt the relationship between agricultural production and agricultural loan performance. We also find that the effects are not symmetric. Restricting attention to those county-years with crop production more than half a standard deviation below their historical county average, the relationship between crop production and agricultural loans past due is nearly twice as large (24 bps) and statistically significant relative to the entire sample. Notably, there is no statistically significant relationship between yields and loans past due for low yield county-years *unless* there is a separate control for indemnifications. The results highlight the importance of accounting for insurance programs when understanding the linkages between climate related financial risks and loan performance outcomes. In placebo tests, we find that there is no significant relationship between either crop yields or indemnifications with commercial and industrial (C&I) loan performance for banks located in the same counties as agricultural banks. The absence of a relationship is consistent with the proposed interpretation that relationships for agricultural banks are not the consequence of other county-time omitted variables. Moreover, the results suggest an absence of measurable spillover effects from crop yields and indemnifications on local bank non-agricultural credit risks.

Using data from the Climate Impact Lab and the empirical estimates, we obtain projections of changes to agricultural loans past due by applying the estimated parameters from the historical relationship to crop yield projections from various climate scenario pathways and different assumptions on the evolution of indemnfications in those scenarios. We find modest nationwide effects of climate change on agricultural loan performance, equal to about a 17 bps increase in past due rates, assuming that insurance programs do not increase commensurately with crop yield declines. However, the national aggregate obscures important regional variation. In particular, we find that agricultural loans past due increase by at least 33 bps in at least one tenth of counties, particularly those located in the Corn Belt and those along the Mississippi and Missouri Rivers. Assuming that current subsidies via crop insurance keep apace with climate change, we find that the effects are attenuated by approximately 68 percent, demonstrating the importance of agricultural finance resilience to the structural parameters of the U.S. crop insurance program.

We argue that the institutional features of agricultural lending may lead to an underestimation of the effects of climate change on agricultural credit risk. For example, carryover debt allows farmers and financial institutions to smooth over short-term cash flow shortages that result from climate, market, or other events into medium and longer-term loans, often backed by farmland. Therefore, short-term stresses on agricultural bank balance sheets resultant from poor production is not always observable to the extent that banks restructure agricultural loans consistent with the common business practices of carryover debt. In an environment with a consistent climate, annual county-level deviations in crop yields are, by assumption, orthogonal to the climate itself. Thus, consistent with regulatory guidance, carryover debt may be in the long-term best interests of the bank and the debtor depending on the circumstances and available collateral (Federal Deposit Insurance Corporation (2020)). Consistent with carryover debt practices, we find that growth in agricultural loan balances backed by real estate correlates negatively with the prior year's crop yields. However, if climate change induces correlations between forward looking deviations from historical crop yields and farmland prices (see, Schlenker, Michael Hanemann, and Fisher (2005)), then the estimates of the effects of crop yields and insurance on agricultural production loan performance likely understates the overall effect of climate change on agricultural banks. Furthermore, federal crop insurance is designed to be actuarially fair, although the federal government pays approximately two-thirds of the insurance premiums. To the extent that poor yields are indicative of broader climate change patterns, future risks may be amplified further as increased premiums could put strain on farm cash flows, and may also be capitalized into farmland prices.

An inherent challenge in any study on the effects of climate-related financial risks is the applicability of estimates on data to forward-looking projections of climate change where there is no historical antecedent. Within the reduced-form setting studied in this paper, we cannot account for adaptive responses of bankers or farmers under a climate change scenario that are outside the historical experience. Anticipating future losses from climate change, banks can restrict credit or change underwriting criteria to dampen losses (Correa, He, Herpfer, and Lel (2022), Sastry (2022)). Finally, technological innovation such as crop resilience can further mitigate the effect of climate change on yields. Moreover, farmers may switch crops to those more conducive to the changing climate (Mendelsohn, Nordhaus, and Shaw (1994), Schlenker and Roberts (2009)): as maize yields decrease in the Corn Belt due to climate change, wheat yields are expected to increase. For example, Rising and Devineni (2020) suggests that agricultural losses are halved under a high emissions scenario from 31 percent to 16 percent through crop switching.

This paper contributes to a growing literature on the role of insurance in climate-related financial risk. Due to the availability of data, the literature primarily considers the real estate market and flood insurance. Sastry (2022) studies the role of flood insurance in mortgage credit supply, while Ge, Lam, and Lewis (2023) studies the capitalization of insurance premiums into real estate prices. The literature also finds that payouts from insurance policies improves loan performance following disasters, including floods, fires, and hurricanes (An, Gabriel, and Tzur-Ilan (2023), Biswas, Hossain, and Zink (2023), Gallagher and Hartley (2017), Issler, Stanton, Vergara-Alert, and Wallace (2020), Kousky, Palim, and Pan (2020)). In contrast, this study examines the role of insurance in the agricultural lending and does not focus on a specific hazard. In the context of crop insurance, annual, county-level coverage and indemnification data provides a rich set of information relative to the frequency and granularity of other insured events.

This paper also contributes to a literature on climate-related financial risk and the agricultural sector. Cornaggia and Li (2022) find that agricultural lending contracts in response to short-term forecasts of extreme temperatures and argue that adaptive responses by agricultural lenders can thereby amplify decreases in crop production due to climate change. Meanwhile, Kahn, Panjwani, and Santos (2024) find that by insulating banks from risk, crop insurance increases bank risk taking. Mendelsohn, Nordhaus, and Shaw (1994) and Schlenker and Roberts (2009) take a Ricardian approach to estimating the effects of climate change on agricultural finance by inferring from farmland prices how farmers optimally adjust production inputs across climate. Mendelsohn, Nordhaus, and Shaw (1994) predict the overall effects of global warming on agriculture to be small as farmers adjust their production inputs, though Schlenker, Michael Hanemann, and Fisher (2005) argue that the effects are considerably larger after accounting for irrigation. Severen, Costello, and Deschenes (2018) show that some of the effects of climate change are already capitalized into farm prices. In contrast to other studies on agriculture lending and farm prices, this study focuses on the effect of weather events on the performance of agricultural loans, the role that insurance plays in attenuating the financial impacts of those events, and the possible amplification of risk through the practice of carryover debt.

We discuss some of the key institutional features of agricultural lending in Section II. Section III discusses the data used in the analysis. In Section IV we discuss the empirical strategy used to related agricultural loan portfolio outcomes to crop yields and crop insurance and use those estimates to project changes in portfolio outcomes under specified climate scenarios. In Section V we discuss the practice of carryover debt in agriculture and potential implications from climate change.

II. Institutional Environment

A. Agricultural Lending

Agricultural lending is an important feature of the agriculture industry. From 2016 to 2019, agricultural debt totaled approximately $400 billion per year, relative to gross agricultural output of about $440 billion per year on average over that time. Of that lending, about 60 percent was backed by real estate. Commercial banks account for about 40 percent of total agricultural lending over that period, comparable to agricultural lending provided through the farm credit system, a government sponsored entity overseen by the Farm Credit Administration.[3] Because the funding models and structures of farm banks differ from commercial banks, we focus on commercial bank agricultural lending for the analysis in this paper.

Agricultural production loans, included in the 40 percent of agricultural loans not backed by real estate, are often self-liquidating. The maturity date of the loan is often tied to the production cycle of the underlying crop or livestock and the loan is repaid with the sale of the associated crop or livestock. Production loans are generally short-term, coinciding with the production cycle for the commodity. Loans backed by farmland or equipment tend to be longer term, though through carryover debt, may become intertwined with the annual production cycle (see more below).

The agricultural cycle differs across commodities. For many crops in the U.S., the canonical production loan is extended as a line of credit around the turn of the calendar year and most of the line is subsequently drawn down in the purchase of materials and planting in the Spring, with harvest of the crop occurring in the Fall.[4] Combined, corn and soybean production comprise the majority of crop production in the U.S. In contrast, agricultural loans supporting cattle, the plurality of animal-related agricultural production in the U.S.,[5] might support the breeding of calves for sale in the Spring or the purchase of calves in the Spring for feeder livestock. In this paper, we focus on crop production due to the availability of historical data and projections under climate change scenarios. We note as a limitation that agricultural loan data is not segmented by agricultural product and provide analysis to assess the implications of the limitation on the results.

[3] U.S. Bureau of Economic Analysis, "U.Gross Output by Industry."
U.S. Department of Agriculture, Economic Research Service. Farm Income and Wealth Statistics, February 7, 2023.

[4] The specifics of the timing depend on the crop and geography.

[5] USDA

B. *Carryover Debt*

When short-term production loans are unable to be paid at their initial maturities, for example due to low crop yields resulting in insufficient income from the crop cycle, the loans may be rescheduled into an intermediate or long-term amortization.[6] This practice of restructuring is referred to as carryover debt. Through carryover debt, farmers smooth risks over the production cycle. Meanwhile, agricultural lenders manage the credit risk of carryover debt by collateralizing the debt with farm assets, which may involve acceptable risk when the farm has sufficient net worth.

The presence of carryover debt complicates the relationships between agricultural credit risk observable on lenders' balance sheets and physical agricultural production (data on carryover debt is not available, so the practice is not directly unobservable in balance sheet data). Rather than resulting in a deterioration in agricultural production loan outcomes, production shortfalls may materialize in a restructuring of loans from production loans to agricultural real estate loans. Consequently, we focus first on agricultural loans past due in the first quarter subsequent to the crop year. We then use the framework of Mendelsohn, Nordhaus, and Shaw (1994) and Schlenker, Michael Hanemann, and Fisher (2005) to understand the implications of climate change for farmland prices. When weather shocks are identically and independently distributed over time, poor production one year due to weather does not affect expectations of future productivity. However, in the context of climate change, agricultural productivity one year may correlate to future productivity and farmland values. We explore the relationship between crop yields and agricultural loans backed by real estate in Section V.

C. *Crop Insurance*

The Federal Crop Insurance Program (FCIP) provides farmers the opportunity to purchase insurance coverage against common financial losses for firms, including adverse weather and market

[6]Federal Deposit Insurance Corporation (2020).

conditions. The federal government subsidizes premiums and the U.S. Department of Agriculture (USDA) regulates and reinsures the policies. In 2019, the FCIP insured approximately 28 percent of all U.S. agricultural production, and over 85 percent for major crops such as corn, soybeans, cotton and wheat. The FCIP is part of a larger safety net for U.S. farms that also include state and private programs, though it accounts for the plurality if not the majority of total safety net support to firms in recent decades. Moreover, corn, soybeans, wheat, and cotton account for a substantial majority of FCIP insured agricultural value.[7]

Climate change has the potential to increase agricultural losses, which could increase total costs of crop insurance. Given that the total premiums for FCIP are calculated to be actuarially fair, an increase in expected losses would result in higher premiums. Furthermore, conditional on using good farming practices for the insured crop, producers cannot be excluded from the program on the basis of risk. Consequently, how increased costs of the FCIP due to climate change pass through to farmers, and potentially their creditors, depends upon the extent to which premiums are paid by farmers and the federal government. In 2021, federal subsidies covered 63 percent of crop insurance premiums, with farmers covering the remainder of the premiums. However, climate change has the potential to increase indemnifications and insurance premiums (Office of Management and Budget (2020)).

III. Data

Agricultural bank data are collected from banks' Reports of Condition and Income (Call Reports) as part of "Loans to finance agricultural production and other loans to farmers." In addition to production loans described above, the item also includes loans made to finance machinery and equipment, loans to fisheries and forestries, and other loans made to finance the operations of the farm. Although the measure is imperfect, it is the closest proxy for agricultural production loans

[7]See, Congressional Research Service (2021).

available in the data and is used for subsequent analysis. Given the production cycle for (most) crops in the United States, we measure past due agricultural loans as the sum of 30 to 89 days past due and 90 days plus past due as of first quarter end, and use other balance sheet variables (such as loan volumes) as the four-quarter average from the prior calendar year. We assign banks to counties based on bank headquarters and restrict attention to agricultural banks with less than $5 billion in assets (constant 2019 dollars) under the assumption that inter-county operations are sufficiently negligible for banks below that size.

Agricultural data are sourced from USDA products. Data on crop insurance derives from USDA Risk Management Agency Summary of Business and Cause of Loss data sets. Summary of Business data include information on policies sold, premiums paid, acres insured, policies indemnified, and total liability across policies by county-crop-year and also by insurance plan type (for example, revenue protection policies versus yield protection policies) and the level of coverage selected (similar to a deductible).[8] We rely upon the USDA Economic Research Service for county-crop production, including acres harvested and acres planted. We use data from Climate Impact Lab on agricultural damages under pre-specified climate scenarios to project our estimates into agricultural loan outcomes. See Section IV.C for additional information.

Given the quality of data on crop production and the variation across geographies in crop yields, we focus our attention on crops. Row crops are the vast majority of FCIP liabilities and therefore make up the majority of indemnities. Our analysis focuses on agricultural banks, defined as banks whose agricultural production and real estate loans comprise at least 25 percent of total loans and leases.[9] The frequency of agricultural bank-years by the state of bank headquarters is reported in Table I. Notably, some states' agricultural production is predominantly in crops (Illinois), while others' agricultural production is divided fairly evenly between crop and animals

[8] Generally, revenue protection policies guarantee a certain level of production revenue by insuring against low output prices and/or a drop in the quantity of production. Yield protection policies insure farmers against a drop in production of a particular crop but does not guarantee the amount of revenue. Revenue protection policies make up the large majority of policy types under the program.USDA, Crop Insurance at a Glance.

[9] The definition is based on the *INSTAG* variable defined in the Research Information System (RIS) maintained by the FDIC.

(Iowa and Nebraska), and others are predominantly animal production (Texas). Consequently, the sample of agricultural banks in our analysis are not necessarily affected directly by crop productivity and indemnifications. We run our analysis separately for counties with a high proportion of crop receipts to total agricultural receipts to test the validity of our findings.[10]

We first construct a measure of physical productivity, q_{cgy}, of crop (c) in county (g) in year (y) as the quantity yield of the crop (physical units of production divided by acres harvested) multiplied by the acres harvested divided by acres planted. Although productivity is often measured as a fraction of land harvested, multiplying by the harvestable fraction allows us to account for additional production variability associated with climatic events (Wei et al. (2023)). We then calculate the average physical productivity of the crop, μ_{cg} as the average of q over the years for which the crop is observed as planted in the county. We also calculate the standard deviation of crop production σ_{cg} for the crop in the county across years. We construct a county-year measure of crop productivity as:

$$\sigma_{gy} = \sum_{c} \frac{plant_{cgy}}{\sum_{c} plant_{cgy}} \frac{q_{cgy} - \mu_{cg}}{\sigma_{cg}} \tag{1}$$

where $plant_{cgy}$ is the number of acres planted for the crop in the county in a year. Thus, σ_{gy} represents the county-specific normalized deviations of physical productivity, weighted by the acres planted for the crop in that year.[11]

[10] We note that there is only one agricultural bank in California, which is the largest agricultural state by receipts. This bank is excluded from our sample based on the asset cutoff used for inclusion. In addition, crops with regular historical data are unrepresentative of certain regions of the country, such as New England. The data limit our ability to test whether the mechanisms in this paper apply to other crops and forms of agricultural finance. Our analysis does not generally reflect agricultural loan outcomes in states whose agricultural production is not covered by FCIP data or states with few or no small agricultural banks.

[11] Due to data limitations, the analysis focuses on seven crops: corn, soybean, cotton, wheat, sorghum, rice, and oats, and occasionally subsetting to the first five as needed due to data limitations.

IV. Empirical Framework

Understanding the role that climate change may have on agricultural banks requires (1) estimates of the effect of climate change on crop yields (2) estimates of the effects of crop yields on crop insurance indemnifications and (3) estimates of the effects of crop yields and crop insurance indemnifications on agricultural loan performance. A full accounting of the effect of climate change on agricultural banks also requires assumptions on (4) the responsiveness of crop insurance programs to climate change, including the incorporation of climate change mitigation processes into eligibility criteria for the program (5) the adaptive responses by farmers and (6) the adaptive responses of financial institutions, each of which have some ability to mitigate the effects of climate change to their business models. Finally, given the practice of carryover debt, a full accounting should also estimate the effect of climate change on carryover debt practices and the effect of climate change on farmland prices, which is likely to be correlated with changes in crop yields due to climate change. Our empirical framework does not address all aspects of these estimates. For (1), we rely on existing literature and focus instead on items (2) and (3). Item (4) requires assumptions about future policy and is beyond the scope of this analysis. Item (5) is embedded within the forecast framework of Climate Impact Lab (discussed more below) and (6) we leave open for future work, and other macroeconomic feedback effects, such as agricultural prices.

A. Relating Crop Yields and Indemnifications to Agricultural Loan Performance

We relate agricultural production past due loans in the first quarter of a calendar year as a proportion of average production loans from the prior calendar year at bank b, headquartered in county g, at time t to past agricultural yields and crop insurance payouts. We restrict attention to agricultural banks with less than \$5 billion in assets.

Indemnified losses are collected from USDA Summary of Business and Cause of Loss Data from the Federal Crop Insurance Program. We use indemnified losses per policy as the measure of payouts. Note that the indemnified losses reflect a combination of the policy coverage levels and policy plans, which include yield and revenue protection. Furthermore, the indemnified losses incorporate the crop price accompanying the plan. For example, for a crop with a Fall harvest, insurance plans may price losses using the maximum of the futures price at planting and a futures price at harvest for December delivery.

We expect yields to correlate negatively with loan past dues. Banks in counties with worse than usual agricultural production are less likely to be able to service their production loans and more likely to result in past due loans in the first quarter following harvest.[12] Conditional on crop yields, indemnification losses are expected to be associated with lower past due ag loans as farmers are able to use proceeds from insurance to service their production loans and lenders commonly take a security interest in the insurance proceeds.[13] We run the following OLS specifications, including our variables of interest, controls, and each including bank fixed effects:

$$AgLoanPastDue_{bgt} = \beta\sigma_{gt} + \gamma_\tau Indem_{gt} + \delta_b + \Gamma Controls + \epsilon_{bt} \quad (2)$$

In Table II, we report regressions of agricultural loan past due rates on deviations from county crop productivity and indemnified losses. We first report the relationship between agricultural loan past due rates and crop production in Column (1), controlling for the national average of agricultural past due loans. We find a statistically significant result, though with marginal economic significance. A one standard deviation decrease in county yields is associated with about a nine basis point increase in agricultural loans past due. In Column (2), we find that the relationship between crop yields and loans past due is about fifty percent larger after accounting for indemnification payouts, which itself has the predicted relationship with loans past due. A one standard deviation increase in indemnification payouts is associated with a seven basis point

[12]First quarter past due ag loans are higher than for any other quarter.
[13]National Ag Law Center

reduction in agricultural loans past due. In Column (3), we add lagged dependent variables and find similar results, noting that dynamic panel bias is likely to be negligible given the length of the time series (Nickell (1981)). We find similar results in Columns (4) and (5) to those in the first two columns after incorporating year fixed effects. However, we prefer specifications with macroeconomic controls for the variable of interest rather than using year fixed effects, as it allows us to exploit annual variation in crop yields, which is arguably orthogonal to the business cycle more broadly.

In Columns (6) and (7) of Table II we report results for the subsample of bank-years for which crop productivity is at least 0.5 standard deviations below average. Without controlling for indemnification payouts in Column (6) there is not a statistically significant relationship between crop deviations and loans past due. Controlling for indemnification payouts in Column (7), we find that a one standard deviation decrease in crop productivity is associated with a 24 basis point increase in loan past due, more than two and half times the relationship in Column (3). Thus, indemnifications appear to play a significant role in blunting the relationship between crop production and bank loan outcomes. In contrast, in Column (8), we find that for banks with crop productivity at least 0.5 standard deviations above average there is no relationship between either crop production or indemnifications and bank agricultural loan outcomes.[14]

Finally, in Columns (9) and (10), we report results separately according to the county average crop dependency for agricultural production, measured as the county average crop receipts to total agricultural receipts over the period.[15] Agricultural loans past due for banks in counties in the top quartile of crop dependency have a strong relationship with county crop yields and crop indemnifications, while those in the bottom quartile do not demonstrate a significant correlation.

Collectively, the results from Table II demonstrate a connection between agricultural banks' agricultural loan portfolios and physical crop production. In addition, the results demonstrate

[14]Results using magnitude thresholds larger than 0.5 are associated with economically larger results for negative crop deviations, at the expense of statistical power.

[15]Data on receipts is from Bureau of Economic Analysis.

that the strength of the relationship is mitigated by the presence of crop insurance. Consequently, projecting the effects of changes in crop yields as a result of climate change necessarily requires assumptions on the role of crop insurance under the specified climate change scenario.

B. Placebo Tests

Although our results are not causal, it is still possible that they are driven by county-year factors unrelated to agricultural production and indemnifications. We demonstrate that this is not the case by conducting a parallel analysis to Table II, but focusing on C&I loans rather than agricultural loans. A failure to reject the null that crop productivity and indemnifications do not affect non-farm business loans is consistent with the interpretation that their relationships with agricultural loans past due in Table II are not the consequence of broader banking and economic variables.

In Table III we show that the results from Table II are specific to agricultural banks' agricultural loan portfolios. In Columns (1) through (3), we examine past due loans C&I loans at agricultural banks, restricting attention to banks with non-trivial C&I loan portfolios (defined as those with balances of at least one percent of bank assets). In each specification, we find no relationship between agricultural productivity and C&I loans past due at agricultural banks. In Column (2), we find a marginally significant relationship between county-level indemnification payouts and C&I loans past due, though the relationship is not robust to the inclusion of a lagged dependent variable in Column (3).

In Columns (4) through (6), we examine the relationship between C&I past due loans at commercial lending specialist banks—defined as those with at least 25 percent of loans classified as C&I, multifamily residential, construction, or non-residential real estate—and agricultural production, restricting attention to only those commercial lending specialists that operate in the same county as an agricultural lending specialist. In each case, we find no relationship between agricultural productivity and C&I loans past due. In Column (5), we find a marginally significant relationship between indemnifications and C&I past due loans, though the relationship is not robust to the inclusion of a lagged dependent variable.

In Columns (7) through (9), we restrict attention to counties with high levels of agricultural production where we found the largest relationship between our variables of interest and past due loans for agricultural loans at agricultural banks. In each case, we find no relationship between crop productivity and C&I past due loans or indemnification payouts.

Overall, Table III supports the interpretation that the findings in Table II are not the consequence of general county-year macroeconomic or banking conditions. At the same time, it is plausible that crop productivity and indemnifications in a county-year produce spillover effects. Farmers who are are unable to service their loans might also reduce personal consumption and investment. Farmers who received indemnifications for poor production may also generate local economic activity relative to the counterfactual where they bear higher losses. The absence of findings in Table III suggests an absence of measurable spillovers in the county-year data from crop production and indemnifications in the historical sample.

C. Projected Agricultural Loans Past Due from Climate Change Scenarios

Climate scenario analysis is a common tool used to quantify effects of climate change on economic and financial variables using plausible climate scenarios. The approach uses modeled climate (and economic) variables for a particular scenario as inputs and uses modeled parameters from historical data to translate the inputs into financial costs (Brunetti et al. (2022)).

We conduct a climate scenario analysis using data from Climate Impact Lab county-level data (developed by Hsiang et al. (2017)) on agricultural damages to translate our findings into point estimates for agricultural financial direct stress from climate change. Summarized briefly, the authors build county-level projections for daily temperatures and precipitation across three Representative Concentration Pathways (RCPs) commonly used elsewhere in the climate science literature, referenced based upon carbon concentrations that deliver global warming on average at different watts per square meter across the planet (2.6, 4.5, and 8.5). The data provided are based upon RCP 8.5, a high warming scenario. Drawing from distributions of climate realizations consistent with a chosen pathway, the authors project onto outcome variables (such as agricultural yields) using historical relationships from past monthly climatologies from 1981 to 2010. Notably, the agricultural damage functions used in this analysis implicitly assume farmers adapt to climate on a forward-looking basis in a manner similar to past practices. The authors note that, "[f]or example, if farmers have been adjusting their planting conditions based on observable rainfall, the effect of these adjustments will be captured by our results. If climate change poses greater adaptive challenges than in the past, then the estimates will be understated. On the other hand, if climate change prompts more public or private coordination for adaptation, then results may be overstated."

We project the RCP 8.5 scenario onto agricultural loans past due as follows. First, we estimate the historical relationship between indemnifications and crop-weighted (by planted acres) county-level deviations in crop yields, including county fixed effects and county-time-varying insurance coverage levels and recover a correlation of -0.00521. We use this as the baseline historical relationship of indemnification payouts to yields. Next, we map county-level changes in agricultural yields from Hsiang et al. (2017) into county-specific standard deviations from historical norms. On average, we find that climate change under RCP 8.5 is associated with a one standard deviation decline in crop production across counties by 2080 to 2099. We feed the resulting county-level crop yield deviations into the parameter estimates from Table II and under alternate assumptions on indemnification policies (that is, under no changes to indemnification levels or using the historical relationship to adjust county-level indemnifications to changes in agricultural yields).[16]

On a planted-acres weighted average basis across counties, we calculate an increase in 5 bps for agricultural loans past due assuming that insurance keeps apace with climate change and an increase in 17 bps for agricultural loans past due assuming that indemnification levels are held constant. The values reflect a perpetual increase in agricultural loans past due of 0.25 to 0.85

[16] Although the exercise is instructive, we note that the insurance parameters are not causal in nature.

standard deviations from their 2000 to 2019 levels. In the case where indemnifications adjust, we ignore the role that increased premiums might play on farm cash flows and loan performance, which likely leads to an understatement of the effect of climate change on outcomes and an overstatement of the role of an insurance program where premiums are expected to adjust.

The effects of climate change on agricultural loan performance are not distributed evenly across the nation. In Figure 1 we map changes to agricultural loans past due using the Climate Impact Lab estimates on climate change related changes to projected agricultural yields. The map reports projections for a no-additional insurance scenario, in which we assume that there is no *additional* increase in crop insurance indemnifications that reflect higher losses associated with climate change. The estimated effects of climate change on agricultural loan performance vary significantly across the country, consistent with differences in projections from Hsiang et al. (2017) and also reflective of differences in crop yield consistencies across counties that are used to map the forecasts into σ. Under RCP 8.5, we project that agricultural loan delinquencies increase by at least 33 bps for about a tenth of all counties, with the vast majority of those counties lying in the Corn Belt and along the Mississippi and Missouri Rivers. Under the assumption that insurance indemnifications increase in a manner consistent with past relationships of indemnification and yields, the estimates are approximately 68 percent lower.

In Figure 2, we present results from projecting the alternative RCP scenarios and time periods into agricultural loans past due using the empirical estimates.[17] Available scenarios are RCP2.6, RCP4.5, RCP6.0, and RCP8.5 for years 2020 to 2039, 2040 to 2059, and 2080 to 2099. Projections are available at each percentile of the distribution for each scenario and period. Each figure plots agricultural loans past due at the median, 75th percentile loss, and 95th percentile loss. Figure 2a plots the weighted average by 2019 acres planted agricultural loans past due across the United States for the selected percentiles of the distribution, across scenarios and time periods. Given the observation from Figure 1 that losses are particularly large in the Corn Belt, we similarly plot the

[17] Available at Zenodo.

projections in Figure 2b restricting attention only to Iowa. Projected increases in agricultural loan past due rates are smallest for RCP2.6 and remain below 15 bps even at the 95th percentile of the distribution through the end of the century. In contrast, for RCP4.5 and RCP6.0, losses at the tail end of the distribution remain below 20 bps through 2059, but are above 30 bps and 20 bps, respectively, at the 95th percentiles of the distributions in 2080 to 2099. Increases in agricultural loans past due at the 75th and 95th percentile are more apparent for RCP8.5. Consistent with the observation that agricultural production in the Corn Belt is more affected by climate change, projections in Figure 2b are generally higher than those in Figure 2a (note the difference in y-axis scales between Figures 2a and 2b). By the end of the century, the 95$^{\text{th}}$ percentile agricultural loans past due increase nearly 20 bps under RCP2.6. Although the increases in loans past due are generally somewhat higher in Iowa than they are nationally, the patterns across the distribution, time, and scenarios are generally comparable to the corresponding national projections.

Projected increases in agricultural loans past due for RCP4.5 are not necessarily lower than RCP6.0. This is a consequence of nonmonotonicity of agricultural losses across scenarios. It is beyond the scope of this paper to evaluate the different channels that might contribute to the nonmonoticity of climate scenarios to agricultural yields. However, one possibility of a positive feedback mechanism is the role of CO_2 fertilization in agricultural production. For example, Taylor and Schlenker (2021) find that increased CO_2 was the dominant driver of agricultural yield growth in the postwar era and that a 1ppm increase in CO_2 equates to a 0.4 percent, 0.6 percent, and 1 percent yield increase for corn, soybeans, and wheat, respectively. Other studies tend to show smaller yield growth effects (Ainsworth and Long (2021)).

C.1. Vulnerable Communities

In studying climate-related financial risks, policymakers and researchers recognize that the effects may be borne disproportionately by vulnerable communities. Variability among the groups most affected by climate change can affect the extent to which economic agents are able to adapt to climate change or bear the associated losses. Existing research finds that certain communities are disproportionately affected by climate change with respect to health outcomes, labor outcomes, and financial outcomes.[18]

In this subsection, we evaluate whether the agricultural losses depicted in Figure 1 disproportionately affect certain agricultural communities. Understanding which communities are most affected is a descriptive exercise. However, given the large number of covariates that may relate to agricultural financial risk associated with climate change, it is also valuable to understand the robustness of the relationships between measures of vulnerability and agricultural climate related financial risk, as measured using the RCP 8.5 scenario.

We use two variable selection techniques to understand which covariates are most predictive of agricultural loans past due from the scenario analysis (AgRCP8.5). First, we collect 43 variables from National Agricultural Statistics Survey 2017 Agricultural Census, denoted by $\mathbf{X^{NASS}}$. We select variables with sufficient overlap with the counties for which we have a value for AgRCP8.5 and normalize all variables for consistent interpretation. The variables that we include are listed in Table IV. We then run two variable selection techniques on the variables to determine which are most predictive. We do not use the techniques for inference. The specification of interest is:

$$AgRCP8.5 = \mathbf{X^{NASS}}\beta + \varepsilon \tag{3}$$

and the goal is to select $\tilde{\mathbf{X}} \subset \mathbf{X^{NASS}}$ that satisfy some selection criteria to reduce the dimensionality.

First, we use a stepwise regression. In a (backwards) stepwise regression, the outcome variable is first regressed on the entire set of variables, $\mathbf{X^{NASS}}$, as in Equation 3. If any variables have a p-value below a significance threshold (which we set at 0.05), then the least significant variable is dropped. The regression is then run again without that variable and the process repeats until all

[18] For health and labor outcomes see EPA (2021). Climate Change and Social Vulnerability in the U.S. For financial outcomes see Avtar et al. (2021).

remaining variables are statistically significant.

Second, we use a lasso method for variable selection. Lasso estimation minimizes the squared error of the regression specified in Equation 3 plus a term, parameterized by λ, that penalizes model complexity–the number of nonzero estimated model parameters. The optimal λ, and the associated model, are selected through the minimization of the cross-validation mean prediction error, m.

In Table V, we report estimates from the stepwise regression (Column 1) and lasso estimation (Column 2). The normalization of the variables implies that each coefficient can be interpreted as the conditional relationship of a one standard deviation increase in the covariate in standard deviations units of the outcome variable. With respect to vulnerability, counties with larger farms and those with higher revenue are associated with lower agricultural loans past due in the climate scenario using both variable selection approaches. Counties with more farms that are rented and farms that are not occupied by the farm owner are both associated with higher agricultural loans past due. Collectively, the direction of these variables suggests that those farms with the least resources are at higher risk.

With respect to demographic variables, there are few racial, age, or gender characteristics that have a consistent relationship to loan outcomes. One exception is the percentage of farms with Latino operators, which is associated with better agricultural loan performance.

Consistent with Figure 1, there is also a strong relationship between the types of crops planted in a county and agricultural loan performance under RCP 8.5. Corn (grain) and soybeans, both of which are heavily planted in the upper Midwest, are associated with poorer agricultural loan performance under the scenario, while wheat is associated with better loan performance under the scenario. Regions with more cattle per acre are also associated with poorer agricultural loan performance, likely reflecting other local characteristics that are associated with differential exposure to climate risk.

D. Other Bank Outcomes

In addition to affecting loan performance, crop yields and indemnifications may affect bank liquidity. When proceeds from harvest are unable to service production loans or when loans are restructured, bank balance sheets are expected to be less liquid relative to the counterfactual when harvest proceeds can service agricultural debt. Table VI examines agricultural bank outcome variables beyond past due agricultural loans. In Columns (1) through (3), we report results of OLS regressions similar to Equation 2, using the change in bank cash to assets ratio as the outcome variable. In Column (1), we find a negative association between changes in bank cash ratios and crop yields, suggesting that banks increase cash balances following poor agricultural production. However, in Columns (2) and (4), after controlling for indemnification payouts, there is no statistical or economically meaningful relationship between crop production and changes in bank cash ratios. Thus, crop insurance appears to have historically blunted the relationship between crop production and bank liquidity.

In Columns (5) through (8) we report the results of similar regressions using total bank loan growth as the outcome variable. In all cases, we find that crop production does not relate to loan growth in the subsequent year. However, we find that indemnification payouts do relate to loan growth in the following year. Thus, it appears that agricultural banks are better able to support future loans when insurance payouts are greater.

V. Correlated Risks: Carryover Debt and Farmland Prices

Carryover debt is a common practice in agricultural lending. Often, carryover debt refers to production or feeder livestock loans that are unable to be paid at their initial, short-term maturity, and which are rescheduled into an intermediate or long-term amortization. There are a number of circumstances that can lead to carryover debt, including poor crop yields from weather conditions or unexpected low commodity prices. Carryover loans are generally restructured to a longer term amortization, depending upon the available collateral and the borrower's credit quality, among other variables (Federal Deposit Insurance Corporation (2020)).

Carryover debt may lead to understated effects of crop yields and crop insurance indemnifications on agricultural credit risk. In particular, carryover debt allows farmers and financial institutions to smooth shocks to production across production years. Under a stable climate, annual deviations to weather are, by assumption, uncorrelated to future agricultural productivity and securing a past due production loan to sufficient farmland collateral may be in the long-run best interests of the bank and the debtor (Federal Deposit Insurance Corporation (2020)). However, in the context of climate change, annual production deviations from historical averages may correlate with future productivity, thereby affecting the current or future value of farmland against which an unpaid production loan might be collateralized.

We first demonstrate that crop yields correlate negatively with subsequent agricultural real estate loan growth, consistent with the practice of carryover debt. In Table VII, Columns (1) and (2), we report results of regressions of real estate agricultural loans on county-normalized production yields, σ. Consistent with the practice of carryover debt, we find that agricultural real estate loan growth is negatively correlated with crop yields: lower productivity yields are associated with increases in agricultural real estate loans year over year growth in first quarter subsequent to the typical Fall harvest.

Next, we show in Columns (3) through (6) that prior years' financial stress on agricultural production loans is associated with agricultural net charge-offs in subsequent years. This is consistent with the interpretation that charge-offs in agricultural production loans may be the consequence of multiple years of poor production and after carryover debt options have been exhausted. Thus, poor crop yields in the prior year can materialize in charge-offs for agricultural loans in subsequent years, as agricultural lenders are less capable of continuing to rely on carryover debt to continue to smooth shocks across years. However, we note that there is limited variation in agricultural loan charge-offs, with more than sixty percent of bank-years reporting zero net agricultural loan charge-offs. We argue that because carryover debt is a common practice in agricultural lending, its use could be cofounded with low charge-offs, including no charge offs reported at a majority of banks.

Productivity shocks associated with climate change are likely to affect future productivity and farmland values. By rolling nonperforming loans into farmland-backed loans, carryover debt may therefore exacerbate the risks of agricultural lending. To evaluate the extent of correlated risks from carryover debt to exacerbate climate-related financial risk, we first adopt the hedonic pricing approach of Mendelsohn, Nordhaus, and Shaw (1994). In particular, we run the following model where the dependent variable, 1982 farmland values, is a function of average seasonal precipitation and temperature. Following Schlenker, Michael Hanemann, and Fisher (2005), we run the model separately for counties based on irrigation and urbanization, as the relationships between climate and farmland prices are dependent on those characteristics. We do not reproduce their results here. The empirical specification of the model is,

$$Price_{1982} = \sum_{m} \left[\beta_{m,1} T_m + \beta_{m,2} T_m^2 + \gamma_{m,1} P_m + \gamma_{2,m} P_m^2 \right] + \Gamma X + \varepsilon$$

where T_m is average historical monthly temperature and P_m is average historical monthly precipitation for January, April, July, and October, and X is a vector of other county controls.

Next, we use county-level predictions for temperature and precipitation by month under alternate RCP scenarios and time horizons. The county-level precipitation and temperature data under alternative scenarios and time periods are from Coupled Model Intercomparison Project Phase 5 (CMIP5) available at climate.gov, hosted by NOAA. CMIP is a standard experimental framework for studying the output of coupled atmosphere-ocean general circulation models and used in the 2018 Fourth National Climate Assessment sponsored by the U.S. Global Change Research Program. We downscale using Localized Constructed Analogs (LOCA). Applying the coefficient estimates from the model, we then obtain projected changes in dollars per acre at the county-level across scenarios.

One challenge with the estimates of changes in farmland values is that it is unclear to what extent farmland values already incorporate the possible effects of climate change. We adopt the modeling framework from the literature using 1982 farmland prices because we expect that climate change expectations have a negligible effect on farmland prices at that time. However, it is plausible that beliefs about climate change are reflected in 2022 prices. From a 2022 perspective, the potential of correlated risks between production loans and farmland prices that arise through carryover debt requires a stand on the extent to which prices already reflect climate change as of 2022. If farmland prices already reflect future expectations about climate change then annual productivity shocks should not affect farmland prices unless those shocks also lead one to update their beliefs about the possible effects of climate change for that location. On the other hand, it is possible that farmland prices have not updated to beliefs about climate change. For example, existing literature demonstrates the role that local beliefs about climate change play in shaping real estate prices (Baldauf, Garlappi, and Yannelis (2020)).

In this paper, we do not test the extent to which climate change is incorporated into farmland prices in 2022. However, we use farmland price changes from 1982 to 2022 to help us gauge whether those counties with the largest predicted effects from climate change, using the estimates from the approach above, are associated with farmland price increases or decreases. Assuming no other changes, updated beliefs about climate change from 1982 to 2022 should lead those counties with the largest estimated downside effects from climate change to have the largest price declines. Figure 3 demonstrates that the opposite is true. Those counties with the largest expected (negative) effects from climate change over the next twenty years under the RCP 4.5 scenario saw the largest price increases over the past 40 years. While it is possible that farmland prices incorporate climate change despite their movements from 1982 to 2022, it is plausible that farmland prices do not fully account for climate change. We use model implied changes to farmland values from 1982, assuming that farm prices have not adjusted to climate change beliefs from 1982 to 2022, as an upper bound. Alternatively, Severen, Costello, and Deschenes (2018) suggest that 50 to 62 percent of the effects of climate change are capitalized into farmland prices.

Using the county-level estimates of farmland price changes under alternative scenarios allows us to examine how carryover debt can create correlated risks in agricultural lending. Figure 1 demonstrates that the largest projected effects of climate change under RCP 8.5 are in the Midwest and in counties that currently are non-irrigated, such as Iowa, where one could view water as a naturally occurring input at a price of zero (Schlenker, Michael Hanemann, and Fisher (2005)). Under a hedonic pricing approach, dryland counties are also the most likely to face declines in farmland prices. Figure 4 plots the projected declines in farm prices under the RCP 8.5 scenario for the 2080 to 2099 period (with extrapolated changes in farm prices above and below 100 percent truncated at 100). We relate the projected changes from agricultural loans past due from Section IV with the projected change in farmland prices at the end of the century under the RCP 8.5 scenario in Figure 5. We plot the median projection for agricultural loans past due on the horizontal axis and the median projection for farmland prices for urban, non-urban irrigated, and non-urban dryland counties. Consistent with the maps, the figure shows a negative relationship between projections for agricultural loans past due and farm prices. To the extent that farmland prices do not entirely incorporate the possible effects of climate change, the negative correlation suggests that the practice of carryover debt can exacerbate risks in agricultural lending, particularly for dryland non-urban counties.

The availability of irrigation plays an important role in the Ricardian pricing approach used by Schlenker, Michael Hanemann, and Fisher (2005) and, consequently, on our analysis of the potential for correlated risks resulting from carryover debt. Irrigated farmland in the United States grew rapidly from 3 million acres in 1890 to more than 58 million acres in 2017, starting with the 1902

Reclamation Act, and continuing with public investment and technological development (Hrozencik and Aillery (2021)). Though the total amount of irrigated farmland in the United States grew by just three percent from 1997 to 2017, there was significant regional variation. Irrigated farmland from 1997 to 2017 grew significantly in the Northern Plains and Mississippi Delta and shrunk in the Pacific and Southern Plains.

Given the central role that irrigation plays in the model, it is important to understand the capacity of farms in dryland counties to adapt through irrigation. For example, growth in the Northern Plains was driven by increased irrigation in eastern Nebraska, which benefits from abundant groundwater resources. The increase in irrigation may also have been prompted by the severe drought in the area from 2011 to 2012. The ability of a region to expand irrigation through natural resources or via federal, state, or local projects, may play an important role in mitigating bank exposures to declining agricultural real estate prices from climate change.

VI. Conclusion

The exposure of banks to climate change and their abilities to manage the associated financial risks depend on the institutional environments in which banks operate. In this paper, we consider two such institutional features of the agricultural lending market: insurance and carryover debt. In both cases, the institutional features resemble those that are likely relevant in other lending markets (in the case of carryover debt, the natural parallel is loan modification).

We find that accounting for insurance is of first order importance when quantifying the relationship of weather events and bank loan performance outcomes. The relationship of crop productivity and loan outcomes is approximately 50 percent larger after accounting for insurance indemnifications. Using the correlations, we project loan performance outcomes to banks under alternative assumptions about the evolution of coverage from the Federal Crop Insurance Program for different climate pathway scenarios. Finally, we demonstrate that carryover debt may exacerbate risk to banks by inducing a correlation between this year's production loan outcomes and farmland backed loans. Together, our results suggest that expectations about insurance coverage and understanding how climate change is capitalized into current farm prices may help inform bank risk management.

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Table I: Bank-Year State Frequencies, Agricultural Banks < $5 billion, 2000-2020. Agricultural banks are defined as banks with at least 25 percent of loans related to agriculture.

State	Freq (%)	Cumulative
Iowa	15.8	15.8
Nebraska	11.1	26.9
Kansas	11.1	38.1
Illinois	11.0	49.0
Minnesota	9.4	58.4
Texas	6.5	65.0
Missouri	5.8	70.8
Oklahoma	4.8	75.5
North Dakota	4.5	80.1
South Dakota	3.7	83.8
Wisconsin	2.7	86.4
Montana	1.9	88.3
Arkansas	1.6	89.9
Other	10.1	100

Table II: Past Due Agricultural Loans to Total Agricultural Loans. Regressions of the ratio of past due agricultural loans to total agricultural loans, for agricultural bank specialists, defined as having at least 25 percent of loans related to agriculture, with less than $5 billion in assets. Past due is measured in the first quarter of the year subsequent to the crop year. σ denotes the normalized deviation of county-crop yields multiplied by the proportion of acres harvested to acres planted, weighted by county-year acres planted by crop. $Indem/Pol$ is the total indemnified losses in the county divided by the number of policies. $PastDueAg_{US}$ is the national past due agricultural loans to total agricultural loans. L denotes a one year lag operator. Columns (1) through (5) report results for all agricultural banks. Columns (6) and (7) report results for agricultural banks in counties with $\sigma < -0.5$. Column (8) reports results for banks in counties with $\sigma > 0.5$. Column (9) reports results for banks in counties in the top quartile of average crop receipts to total agricultural receipts. Column (10) reports results for banks in counties in the bottom quartile of average crop receipts to total agricultural receipts. Errors are clustered at the state level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	AgBanks	AgBanks	AgBanks	AgBanks	AgBanks	LowYield	LowYield	HighYield	HighCrop	LowCrop
σ	-0.000913***	-0.00132***	-0.000874**	-0.000806***	-0.00106***	-0.00140	-0.00242**	0.000125	-0.00243***	-0.00100
	(0.000301)	(0.000374)	(0.000351)	(0.000213)	(0.000301)	(0.000994)	(0.000928)	(0.000940)	(0.000414)	(0.000783)
Indem/Pol		-0.0938***	-0.0601***		-0.0501**		-0.0972***	0.120	-0.109***	-0.0632
		(0.0231)	(0.0198)		(0.0201)		(0.0270)	(0.162)	(0.0260)	(0.0547)
PastDueAg$_{US}$	0.901***	0.843***	0.712***			0.971***	0.854***	0.636***	0.783***	0.704***
	(0.0817)	(0.0758)	(0.0615)			(0.140)	(0.133)	(0.0971)	(0.143)	(0.198)
L.PastDueAg			0.138***							
			(0.0192)							
Observations	21,662	21,662	18,472	21,662	21,662	4,900	4,900	6,243	5,042	4,125
R-squared	0.326	0.327	0.342	0.328	0.328	0.506	0.507	0.447	0.349	0.339
REG	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
BANK FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	NO	NO	NO	YES	YES	NO	NO	NO	NO	NO

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

Table III: Past Due C&I Loans and Agricultural Outcomes. Sample restricted to banks with less than \$5 billion in assets. Past due is measured in the first quarter of the year subsequent to the crop year. σ denotes the normalized deviation of county-crop yields multiplied by the proportion of acres harvested to acres planted, weighted by county-year acres planted by crop. $Indem/Pol$ is the total indemnified losses in the county divided by the number of policies. $PastDueCI_{US}$ is the national past due C&I loans to total C&I loans. L denotes a one year lag operator. Columns (1) through (3) report results for the C&I portfolio of agricultural banks, defined as having at least 25 percent of loans related to agriculture, conditional on C&I loan balances equal to at least one percent of assets. Columns (4) through (9) report results for commercial lending specialist banks, defined as banks with at least 25 percent of loans classified as construction, C&I, multi-family residential real estate, and non-residential real estate. We restrict attention to C&I bank-years located in the same county with at least one agricultural bank. Column (7) through (9) report results for commercial lending specialists banks in counties in the top quartile of average crop receipts to total agricultural receipts. Errors are clustered at the state level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	AgBanks	AgBanks	AgBanks	CIBanks	CIBanks	CIBanks	CI HighCrop	CI HighCrop	CI HighCrop
σ	-0.000142	-0.000761	-0.000159	0.000211	-0.000129	0.000274	4.20e-07	-0.000289	0.000191
	(0.000349)	(0.000536)	(0.000579)	(0.000176)	(0.000230)	(0.000345)	(0.000447)	(0.000477)	(0.000456)
Indem/Pol		-0.116**	-0.0722		-0.0744*	-0.0351		-0.0572	-0.0279
		(0.0487)	(0.0471)		(0.0388)	(0.0418)		(0.0496)	(0.0357)
PastDueCI$_{US}$	1.207***	1.110***	1.028***	1.093***	1.045***	1.030***	1.001***	0.957***	0.706***
	(0.165)	(0.177)	(0.144)	(0.0833)	(0.0756)	(0.0851)	(0.136)	(0.140)	(0.179)
L.PastDueCI			0.0540***			0.0666***			0.118
			(0.0167)			(0.0204)			(0.0773)
Observations	22,107	22,107	18,900	13,418	13,418	11,111	3,666	3,666	2,998
R-squared	0.306	0.306	0.254	0.335	0.335	0.343	0.357	0.357	0.338
REG	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
BANK FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	NO	NO	NO	NO	NO	NO	NO	NO	NO

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

Table IV: Variables Considered in Variable Selection.

NASS Name	Description
y17_M124	Acres of Corn Harvested for Grain as Pct of Harvested Cropland Acreage: 2017
y17_M126	Acres of Corn for Silage or Greenchop Harvested as Pct of Harvested Cropland Acreage: 2017
y17_M127	Irrigated Sorghum for Grain, Harvested Acres, as Pct of Sorghum for Grain, Harvested Acres: 2017
y17_M128	Acres of Sorghum Harvested for Grain as Pct of Harvested Cropland Acreage: 2017
y17_M130	Irrigated All Wheat for Grain, Harvested Acres, as Pct of All Wheat for Grain, Harvested Acres: 2017
y17_M131	Acres of All Wheat Harvested for Grain as Pct of Harvested Cropland Acreage: 2017
y17_M142	Acres of All Cotton Harvested as Pct of Harvested Cropland Acreage: 2017
y17_M143	Irrigated All Cotton, Harvested Acres, as Pct of All Cotton, Harvested Acres: 2017
y17_M149	Irrigated Soybeans for Beans, Harvested Acres, as Pct of Soybeans for Beans, Harvested Acres: 2017
y17_M150	Acres of Soybeans Harvested for Beans as Pct of Harvested Cropland Acreage: 2017
y17_M011	Pct of Farms with Sales of Less Than $10,000: 2017
y17_M012	Pct of Farms with Sales of $10,000 to $249,999: 2017
y17_M013	Pct of Farms with Sales of $250,000 or More: 2017
y17_M016	Average Value of Crops Sold per Acre of Harvested Cropland: 2017
y17_M036	Total Received from Government Payments, Average Per Farm: 2017
y17_M042	Average Total Farm Production Expenses per Farm: 2017
y17_M050	Expenses for Total Labor as Pct of Total Farm Production Expenses: 2017
y17_M051	Expenses for Hired Farm Labor as Pct of Total Farm Production Expenses: 2017
y17_M072	Estimated Market Value of Land and Buildings, Average per Farm: 2017
y17_M001	Number of Farms: 2017
y17_M003	Average Size of Farms in Acres: 2017
y17_M059	Acres of Land in Farms as Pct of Land Area in Acres: 2017
y17_M061	Acres of Irrigated Land as Pct of Land in Farms Acreage: 2017
y17_M068	Acres of All Types of Pastureland as Pct of Land in Farms Acreage: 2017
y17_M071	Acres Enrolled in Crop Insurance Programs as Pct of Land in Farms Acres: 2017
y17_M091	Pct of Farms Operated by Family or Individual: 2017
y17_M092	Pct of Farms Operated by Partnership: 2017
y17_M093	Pct of Farms Operated by Corporation: 2017
y17_M201	Pct of Farms with Internet Access: 2017
y17_M111	Average Number of Cattle and Calves per 100 Acres of All Land in Farms: 2017
y17_M090	Pct of Land in Farms Rented or Leased: 2017
y17_M097	Average Age of Producers: 2017
y17_M098	Pct of Producers 65 Years Old and Over: 2017
y17_M099	Number of Farms with Young Producers, Age 35 Years of Less, as Pct of Number of Farms: 2017
y17_M102	Pct of Producers Not Residing on Farm Operated: 2017
y17_M103	Number of Farms with Female Producers as Pct of Number of Farms: 2017
y17_M104	Number of Farms with American Indian or Alaska Native Producers as Pct of Number of Farms: 2017
y17_M105	Number of Farms with Asian Producers as Pct of Number of Farms: 2017
y17_M106	Number of Farms with Black or African American Producers as Pct of Number of Farms: 2017
y17_M107	Number of Farms with Native Hawaiian or Other Pacific Islander Producers as Pct of Number of Farms: 2017
y17_M108	Number of Farms with White Producers as Pct of Number of Farms: 2017
y17_M109	Number of Farms with Hispanic, Latino, or Spanish Origin Producers as Pct of Number of Farms: 2017

Table V: Agricultural Loans Past Due and Vulnerable Communities. Column (1) reports results of a stepwise OLS regression of projected agricultural loans past due under a RCP 8.5 scenario at the county level on farm demographics. Column (2) reports results of a LASSO OLS regression of projected agricultural loans past due under a RCP 8.5 scenario at the county level on farm demographics.

VARIABLES	(1) Ag Past Due	(2) Ag Past Due
Economics		
Farm Size	-0.104**	-0.132***
	(0.0451)	(0.0481)
Pct Farm Sales >$250K	-0.138***	-0.138***
	(0.0367)	(0.0423)
Pct Farms Rented	0.114***	0.115***
	(0.0348)	(0.0351)
Pct Not Residing on Farm	0.190***	0.128***
	(0.0303)	(0.0365)
Pct Farm Sales $10K-$250K		0.0161
		(0.0258)
Govt Receipts/Farm	0.0854***	0.0966***
	(0.0300)	(0.0310)
Pct Land Irrigated	0.0859***	0.0926***
	(0.0218)	(0.0221)
Pct Acres Enrolled Crop Ins	-0.359***	-0.398***
	(0.0480)	(0.0507)
Estimated Value RE/Farm	0.0793**	0.0982**
	(0.0387)	(0.0413)
Avg Val Crop Sold/Acre		-0.0525
		(0.0883)
Pct Farms Op by Family	0.372***	0.133**
	(0.119)	(0.0590)
Pct Partnership	0.138**	
	(0.0622)	
Pct Farm Op by Corp	0.290***	0.165***
	(0.0698)	(0.0416)
Pct Farms Internet Access	-0.0568**	-0.0571**
	(0.0246)	(0.0264)
Expense/Farm	-0.156***	-0.152***
	(0.0236)	(0.0242)
Labor/Expense	-0.0944***	-0.0745*
	(0.0336)	(0.0417)
Demographics		
Pct Female		-0.0452
		(0.0333)
Pct Native		-0.0377
		(0.0415)
Pct Asian		0.0604
		(0.0434)
Pct Pacific		-0.0816
		(0.0529)
Pct White		-0.0172
		(0.0467)
Pct Latino	-0.0803***	-0.0773**
	(0.0289)	(0.0300)
Number of Farms		-1.122
		(1.705)
Pct < 35 years		-0.0307
		(0.0322)
Pct Farmers > 65 years		0.00567
		(0.0327)
Land Use		
Corn(Grain) Acre Harv/Total Acre Harv	0.454***	0.466***
	(0.0294)	(0.0312)
Corn(Silage) Acre Harv/Total Acre Harv	-0.154***	-0.149***
	(0.0283)	(0.0289)
Wheat Acre Harv/Total Acre Harv	-0.327***	-0.314***
	(0.0243)	(0.0265)
Cotton Acre Harv/Total Acre Harv		0.0434*
		(0.0230)
Soybean Acre Harv/Total Acre Harv	0.307***	0.320***
	(0.0317)	(0.0342)
Farm Acre/Total Acre	0.0707**	0.0899**
	(0.0316)	(0.0364)
Cattle/Acre	0.191***	0.194***
	(0.0297)	(0.0301)
Constant	-0.0931***	-0.117***
	(0.0211)	(0.0329)
Observations	1,374	1,374
R-squared	0.581	0.584
Selection	Stepwise	Lasso

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

Table VI: Cash Balances and Loan Growth. All regressions restrict attention only to agricultural bank specialists, defined as having at least 25 percent of loans related to agriculture, with less than \$5 billion in assets. σ denotes the normalized deviation of county-crop yields multiplied by the proportion of acres harvested to acres planted, weighted by county-year acres planted by crop. $Indem/Pol$ is the total indemnified losses in the county divided by the number of policies. The US subscript denotes is the national value of the variable. L denotes a one year lag operator. Columns (1) through (3) report results of regression with the cash to asset ratio as the dependent variable. Columns (4) through (6) report results of regressions with the change in log loan balances as the dependent variable. Errors are clustered at the state level.

VARIABLES	(1) ΔCash	(2) ΔCash	(3) ΔCash	(4) ΔCash	(5) LoanGr	(6) LoanGr	(7) LoanGr	(8) LoanGr
σ	-0.00126***	-0.000204	0.000524	-0.000233				
	(0.000306)	(0.000288)	(0.000387)	(0.000339)				
Indem/Pol		0.255***	0.0851	0.302***				
		(0.0700)	(0.0627)	(0.0735)				
ΔCash_{US}	0.802***	0.802***		0.907***				
	(0.0500)	(0.0537)		(0.0570)				
L.ΔCash				-0.246***				
				(0.0138)				
L.σ					-0.00161	0.00123	-0.000836	0.00157
					(0.00116)	(0.00158)	(0.00169)	(0.00159)
LoanGr_{US}					0.238***	0.252***		0.247***
					(0.0180)	(0.0176)		(0.0156)
L.Indem/Pol						0.639***	0.404***	0.689***
						(0.170)	(0.138)	(0.178)
L.LoanGr								0.0466***
								(0.0129)
Observations	21,352	21,352	21,352	18,226	18,906	18,906	18,906	18,374
R-squared	0.090	0.093	0.110	0.154	0.216	0.217	0.224	0.217
REG	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
BANK FE	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	NO	NO	YES	NO	NO	NO	YES	NO

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

Table VII: Agricultural Real Estate Loan Growth and Agricultural Production Loan Charge Offs. All regressions restrict attention only to agricultural bank specialists, defined as having at least 25 percent of loans related to agriculture, with less than $5 billion in assets. σ denotes the normalized deviation of county-crop yields multiplied by the proportion of acres harvested to acres planted, weighted by county-year acres planted by crop. L denotes a one year lag operator and $L2$ denotes a two year lag operator. Columns (1) through (2) report results for regressions of growth in agricultural loan balances, measured at the end of the first quarter in the year subsequent to the crop year. US subscripts denote the national variable. Columns (3) through (6) report results of agricultural production loan charge offs Errors are clustered at the state level.

VARIABLES	(1) Growth(AgRE)	(2) Growth(AgRE)	(3) AgCO	(4) AgCO	(5) AgCO	(6) AgCO
σ	-0.00527***	-0.00470***		0.00102		0.000288
	(0.00155)	(0.00158)		(0.00563)		(0.00632)
L.σ_{crop}				0.00567		0.00666
				(0.00443)		(0.00661)
L.PastDueAg			1.112***	1.138***	1.180***	1.205***
			(0.262)	(0.275)	(0.258)	(0.267)
L2.PastDueAg			1.605***	1.581***	1.676***	1.642***
			(0.272)	(0.274)	(0.277)	(0.285)
PastDueAg$_{US}$			46.23***	46.45***		
			(6.565)	(7.817)		
AgRE growth$_{US}$	0.364***					
	(0.0346)					
Observations	21,454	21,454	16,588	15,793	16,588	15,793
R-squared	0.137	0.139	0.194	0.195	0.196	0.197
REG	OLS	OLS	OLS	OLS	OLS	OLS
BANK FE	YES	YES	YES	YES	YES	YES
YEAR FE	NO	YES	NO	NO	YES	YES

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

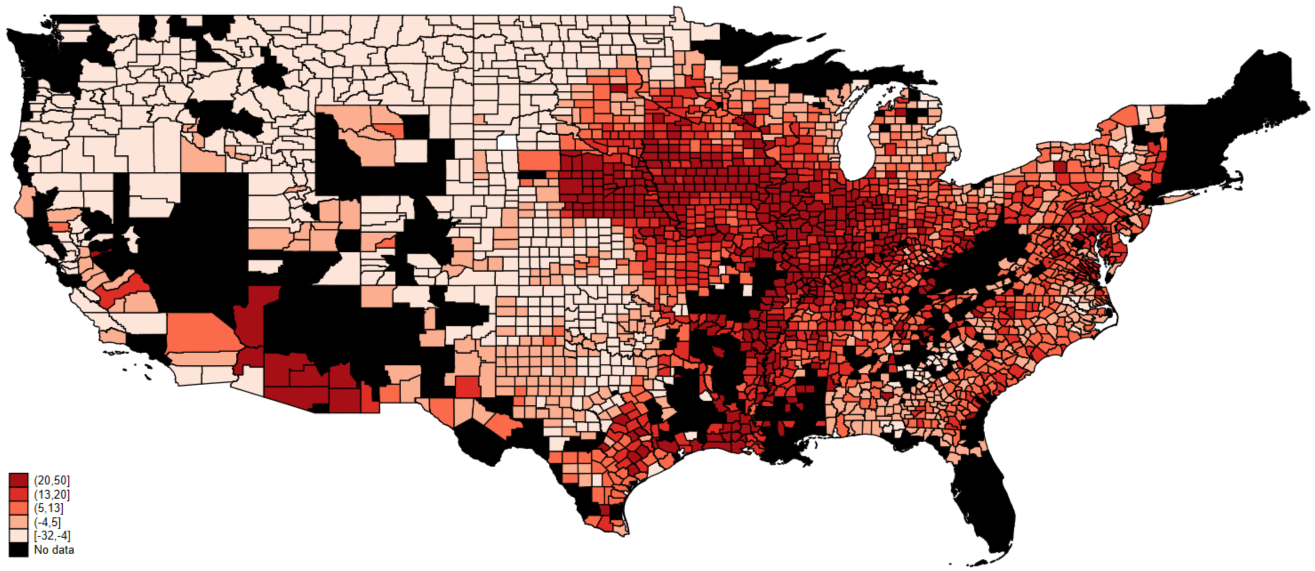
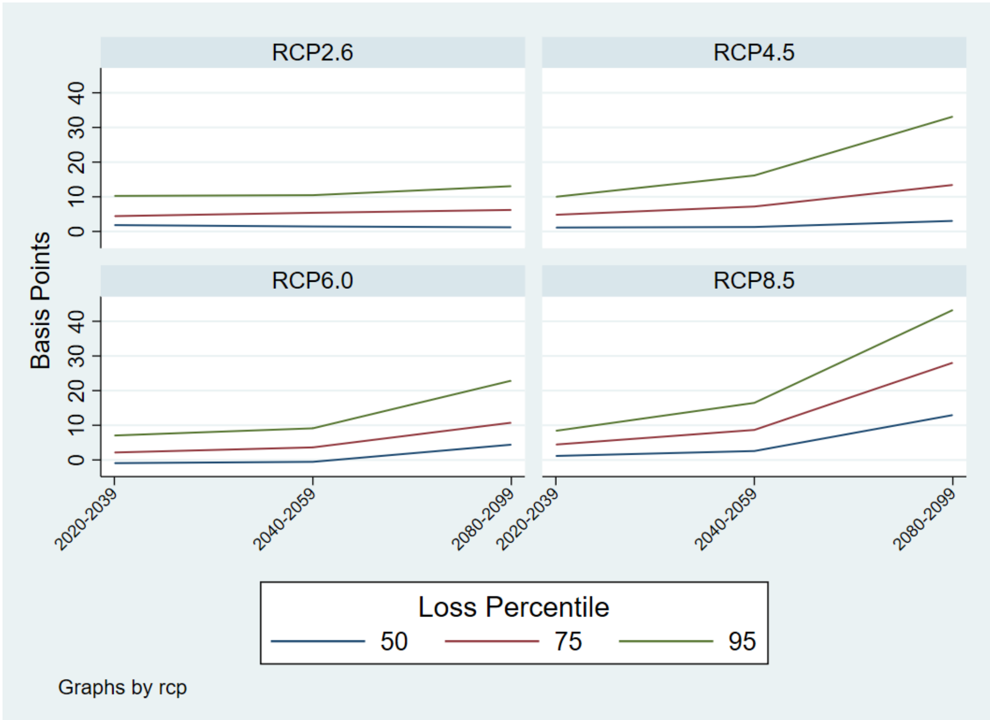
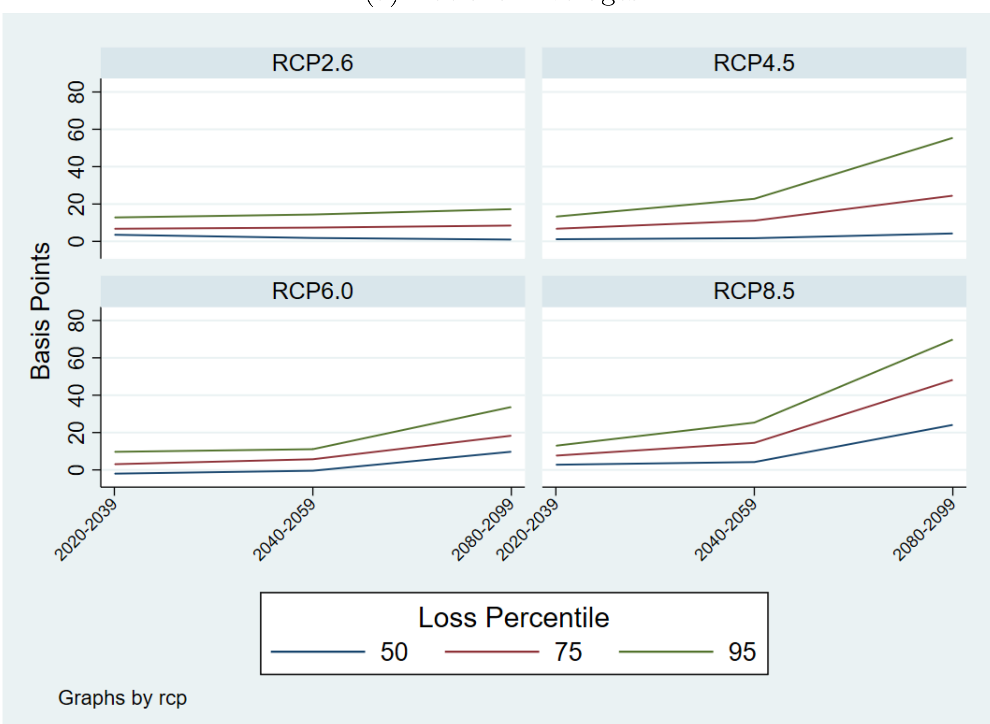


Figure 1: Increase in Agricultural Loans Past Due from Crop Yield Changes Associated with Climate Change Assuming No Increases to Insurance Indemnifications



(a) National Averages



(b) Iowa Averages

Figure 2: Projected Changes in Agricultural Loans Past Due Rates Across RCP2.6, RCP4.5, RCP6.0, and RCP8.5, Weighted Average by Acres Planted in 2019.

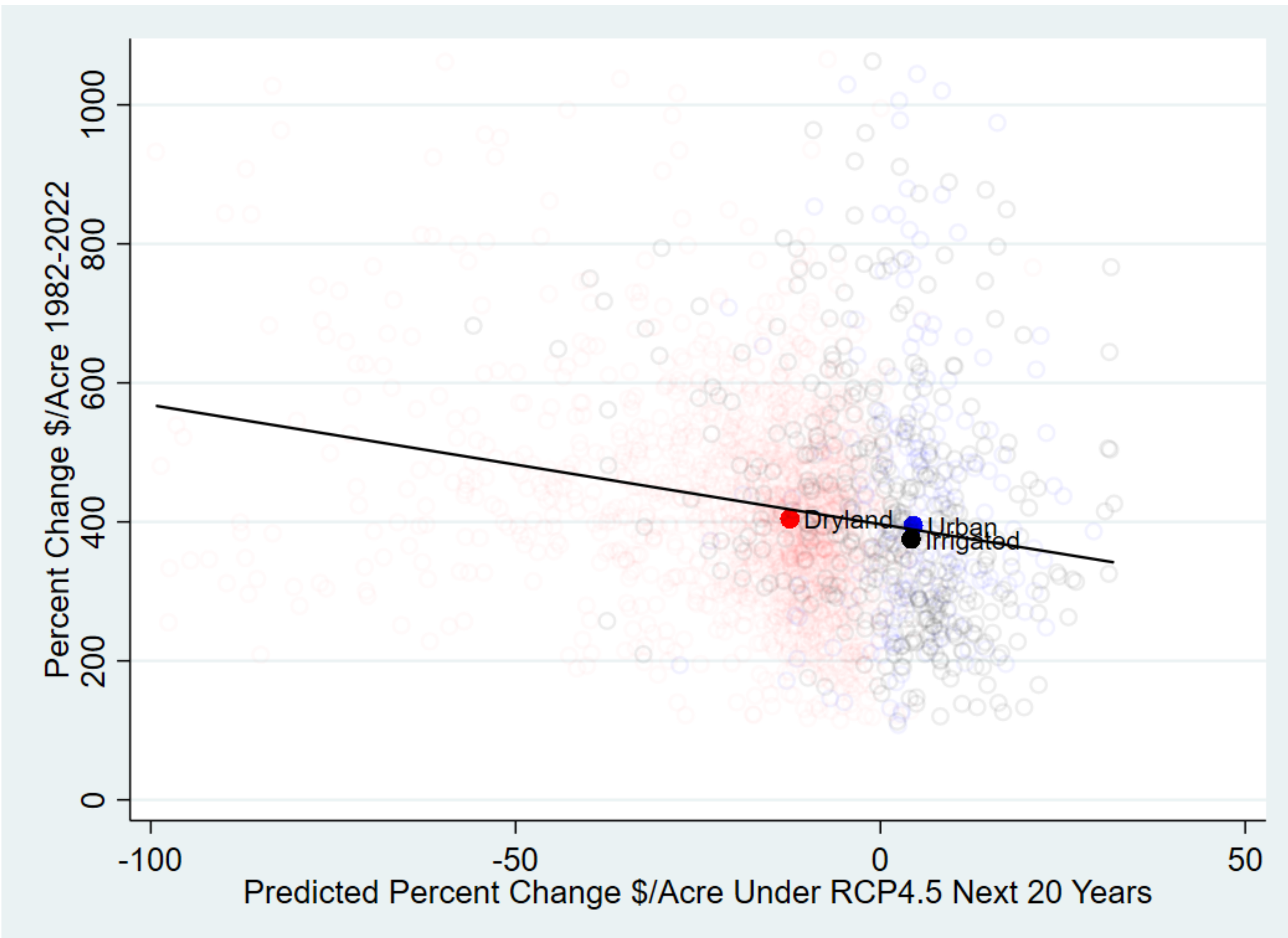


Figure 3: Projected percent changes in farmland prices from 2020 to 2040 under the RCP 4.5 scenario using the hedonic pricing approach of Schlenker, Michael Hanemann, and Fisher (2005) and farmland price changes 1982 to 2022 with an aggregated best fit line. Median values for urban, dryland non-urban, and irrigated non-urban are also plotted.

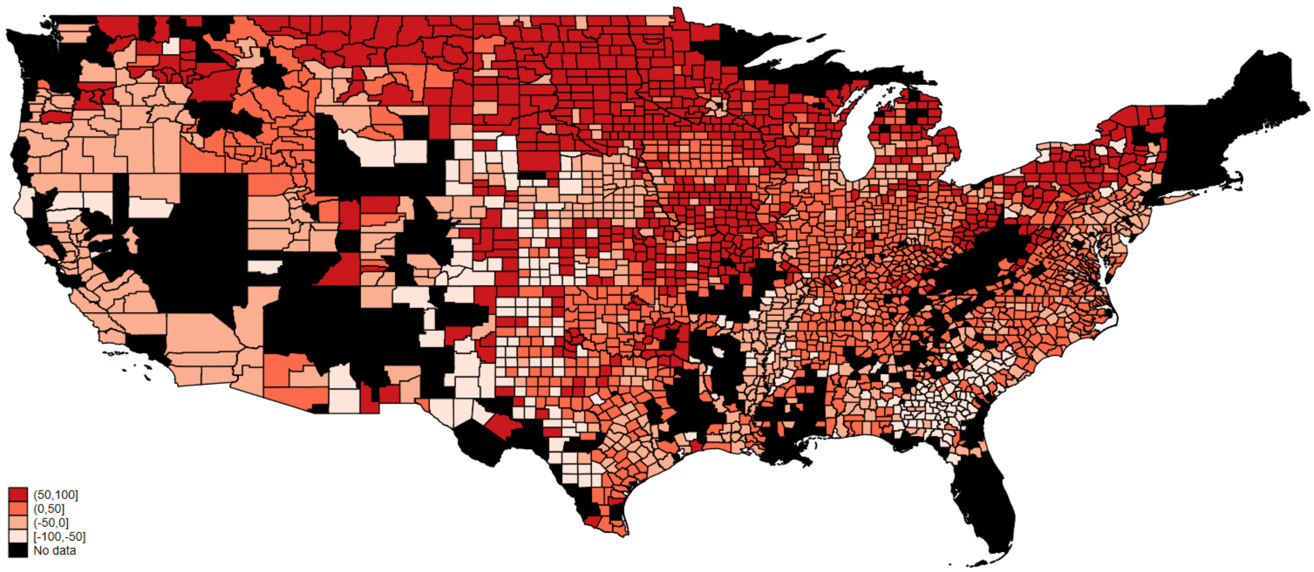


Figure 4: Projected percent declines in farmland prices under the RCP 8.5 scenario for the end of century (2080 to 2099) using the hedonic pricing approach of Schlenker, Michael Hanemann, and Fisher (2005). Values are truncated at -100 and 100. Positive values and darker colors reflect price declines.

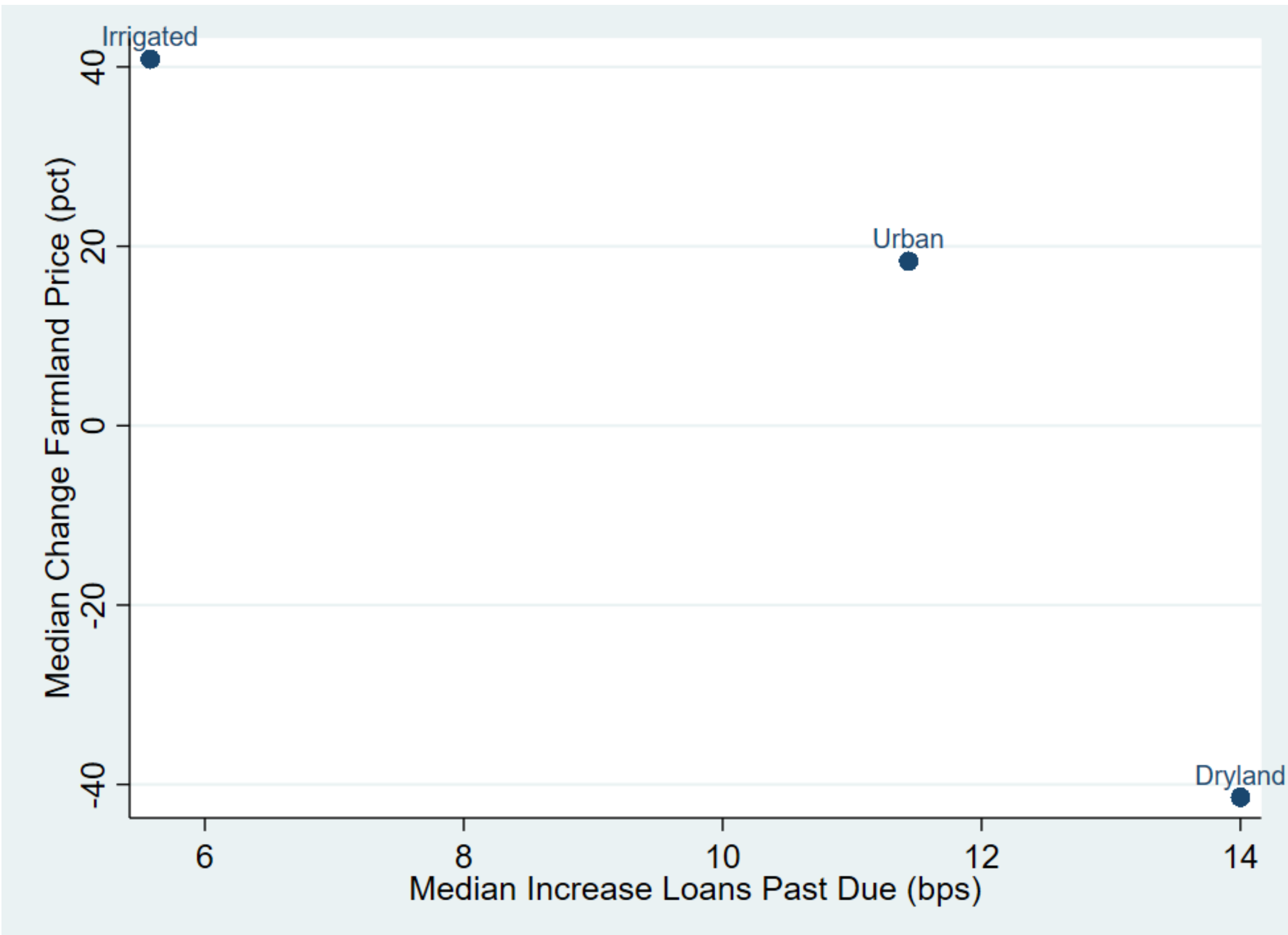


Figure 5: Median projected increases in agricultural loans past due assuming no increases in Federal Crop Insurance coverage and median projected percent declines in farmland prices using the hedonic pricing approach of Schlenker, Michael Hanemann, and Fisher (2005), under a RCP 8.5 scenario for 2080 to 2099.