Payments for Ecosystem Services Programs and Climate Change Adaptation in Agriculture

Youngho Kim
youngk@umd.edu

Department of Agricultural and Resource Economics
University of Maryland at College Park

Abstract. Payments for ecosystem services (PES) programs can enhance crop resilience to extreme weather events by establishing nature-based infrastructure, such as forests and wetlands. This study investigates the effectiveness of the Conservation Reserve Enhancement Program (CREP) in the United States in mitigating flooded crop loss through the restoration of riparian buffers and wetlands. Synthetic control estimates reveal that, during the initial 11 years of program implementation, CREP reduced the number of flooded crop acres by 39 percent and the extent of damage on those acres by 27 percent. Moreover, calculations indicate that the conservation investments made through CREP protected 900,000 crop acres from flooding and generated financial spillover effects to the federal crop insurance program, resulting in savings of $73 million in indemnity payouts that would have otherwise been paid to insured farmers in the absence of CREP. The loss mitigation benefits varied spatially and temporally, influenced by factors such as the duration of program availability, the extent of program participation, and the adoption of alternative risk management strategies. Overall, these findings underscore the critical role of PES programs and natural infrastructure in facilitating climate change adaptation.

Keywords: climate change adaptation, loss mitigation, flood risk management, nature-based infrastructure, payments for ecosystem services, agri-environmental programs

JEL Codes: Q15, Q28, Q54, Q57, Q58

Selected Paper prepared for presentation at the 2023 Agricultural & Applied Economics Association Annual Meeting, Washington DC; July 23-25, 2023

1. INTRODUCTION

Extreme weather events pose a significant threat to agriculture, resulting in substantial payments for disaster relief and crop insurance indemnities worldwide (Carter et al., 2018; Lobell et al., 2014; Ortiz-Bobea et al., 2021; Rosenzweig et al., 2002). To mitigate and adapt to weather anomalies associated with climate change, current political efforts are increasingly focused on restoring nature-based infrastructure, such as forests and wetlands, which requires land use adjustments to existing agricultural land (e.g., Biden-Harris Administration's Nature-Based Solution Roadmap at COP 27). In making such efforts, payments for ecosystem services (PES) programs can play a central role by providing financial incentives to farmers and landowners for adopting long-term conservation practices on their agricultural land.

PES programs have been widely implemented to provide a variety of environmental amenities to society, such as reduction of agricultural nonpoint source water pollution and carbon sequestration benefits (see Alix-Garcia & Wolff, 2014; Baylis et al., 2022; Jack et al., 2008; Ribaudo & Shortle, 2019; Wunder et al., 2020 for reviews). In addition to the environmental benefits, there is evidence that conservation practices can build crop resilience to extreme weather events associated with climate change, such as flooding and drought (Kousky & Walls, 2014; Michler et al., 2019; Taylor & Druckenmiller, 2022). For instance, the restoration of riparian buffers and wetlands on agricultural land can attenuate regional flood risks by absorbing excess water, while cover crops and conservation tillage can help manage soil moisture during droughts (Acreman & Holden, 2013; Basche & DeLonge, 2019; Brody & Highfield, 2013; Croke et al., 2017; Delgado et al., 2011; Spalding et al., 2014). However, research on the potential contribution of PES programs to climate change adaptation in agriculture remains limited (Karwowski, 2022; Kousky et al., 2013).

In this study, I examine to what extent the introduction of PES programs mitigates crop losses under extreme weather events. My analysis focuses on investments made through the USDA's Conservation Reserve Enhancement Program (CREP) in streambank and wetland restoration practices. Since its establishment in 1998, CREP has played a central role in reducing agricultural nonpoint source water pollution and preserving wildlife habitat in selected watershed regions across the United States. For instance, the program primarily converts environmentally sensitive cropland and marginal pastureland near waterbodies into protective buffers and wetlands that are highly effective in filtering nutrient runoff and reducing regional flood risks. CREP invested a total of $1.6 billion (in nominal terms) to establish and maintain approximately 1 million acres of conservation practices nationwide during the fiscal years of 2013-2022. To the best of my knowledge, however, this paper is the first empirical investigation into the loss mitigation benefits associated with the introduction of CREP.

To estimate the loss mitigation benefits of the PES program, I exploit county-level spatial and temporal variations in the introduction of CREP and flooded crop loss across 384 counties in the Mississippi River Basin from 1989 to 2022, using panel data from the USDA's Farm Service Agency (FSA) and Risk Management Agency (RMA). The introduction of CREP to an individual county is jointly determined by the federal and state government due to their regional or national environmental and resource concerns such as declining wildlife habitat or nutrient pollution in the Gulf of Mexico, rather than the county's crop loss experience. During the first 11 years of program implementation in 243 counties in the Mississippi River Basin, the government invested a total of $440 million to establish and maintain 280,000 acres of conservation practices such as riparian buffers and wetlands.

The ideal experiment for assessing the loss mitigation benefits of CREP would involve comparing flood damage on cropland between counties that are identical in all aspects, except for the presence of CREP. However, my identification strategy faces two empirical challenges. First, the availability of CREP may be associated with other factors that contribute to flood damage on cropland. For instance, counties with higher levels of flooded crop loss may also reap greater water quality benefits when nature-based infrastructure is established, leading to the implementation of CREP. In addition, the staggered rollout of CREP with heterogenous program effects across counties requires careful selection of a comparison group to avoid bias in the estimated causal effect (Baker et al., 2022; Borusyak et al., 2021; Goodman-Bacon, 2021; Roth et al., 2023). To address these identification challenges, I employ a partially pooled synthetic control method (SCM) with an intercept shift (Arkhangelsky et al., 2021; Ben-Michael et al., 2022). The program effect estimator takes the form of a weighted difference-in-differences (DID) estimator, while it aims to achieve parallel pre-policy trends in outcomes between the treated and control groups. Key identification assumptions generally align with other weighted DID estimators such as the absence of (i) time-varying confounding factors, (ii) policy anticipation effects, and (iii) spillover policy effects (Callaway & Sant'Anna, 2021; de Chaisemartin & d'Haultfoeuille, 2020; Sun & Abraham, 2021).

I find economically and statistically significant loss mitigation benefits of conservation investments made through the introduction of CREP. Synthetic control estimates indicate that, on average, the introduction of CREP reduced the number of flooded crop acres by 39 percent and mitigated the extent of crop damage on those acres by 27 percent during the first 11 years of program implementation. Calculations using the estimated program effects suggest that CREP protected 900,000 crop acres from flooding and saved $73 million in indemnity payouts that would have been paid to the insured farmers in the absence of the program during the same period.

I also find that the magnitude of flood mitigation benefits varies spatially and temporally depending on several factors. For example, loss mitigation benefits generally grow with the duration of the program availability. Specifically, the reduction in indemnity payouts per flooded crop acre starts at 21 percent during the initial five years of program implementation and increases to 30 percent during years six to eleven. The sources of this increase are twofold. First, the adoption of conservation practices increases as program participation rises over time. Second, the effectiveness of established conservation practices improves over time due to the maturation of vegetation on riparian buffers and wetlands. The loss mitigation benefits are also greater in counties that (a) are heavily dependent on crop insurance to manage production risk, (b) are located downstream in the Mississippi River Basin, and (c) have little flood protection from levees. These findings are qualitatively robust to sensitivity checks in the estimation of program effects.

This paper contributes to the growing literature on climate change adaptation in agriculture (Ortiz-Bobea, 2021). Prior studies identified a lack of adaptation in U.S. agriculture and projected increased agricultural productivity losses due to the intensification of extreme weather events such as drought and flooding (Burke & Emerick, 2016; Lobell et al., 2014; Ortiz-Bobea et al., 2018). The empirical evidence presented in this paper demonstrates that nature-based infrastructure established through PES programs can play a pivotal role in mitigating crop losses under anticipated weather anomalies resulting from climate change. These findings support ongoing global initiatives to restore natural ecosystems for climate change mitigation and adaptation. In addition, the analysis has direct implications for managing flood risks in a major crop production region in the United States.

This paper also contributes to a broader understanding of the interaction between existing policies (Fischer & Preonas, 2010; Fleming et al., 2020; Ifft et al., 2019). The conservation program and the federal crop insurance program accounted for two-thirds of the projected cost of the 2018 Farm Bill ($29 billion and $38 billion, respectively) excluding the nutrition program. Thus, it is important for policymakers to comprehend the potential interaction between these two programs. Previous studies have explored whether the federal crop insurance program disincentives farmers to adopt loss mitigating strategies against weather anomalies (Annan & Schlenker, 2015; Di Falco et al., 2014; Fleckenstein et al., 2020; Mcleman & Smit, 2006; Prokopy et al., 2019). In addition, they examined how the heavily subsidized crop insurance affects agricultural conservation and environmental outcomes (Claassen et al., 2017; Connor et al., 2021; DeLay, 2019; Feng et al., 2013; Miao et al., 2016; Schoengold et al., 2015; Wu, 1999; Yu et al., 2022). This paper examines the converse and shows that the introduction of a PES program may reduce production risks and improve the sustainability and financial performance of existing risk management programs including the crop insurance program.

The findings of this study have important implications for future research and existing policies. Existing benefit cost analyses of PES programs have mainly focused on the additional environmental benefits and the cost of conservation (Claassen et al., 2018; Ferraro & Simpson, 2002; Fleming et al., 2018; Lichtenberg, 2021; Lichtenberg & Smith-Ramirez, 2011; Mezzatesta et al., 2013). This paper, however, suggests that future analyses should also consider the long-term benefits of PES programs on crop productivity and the economic spillover effects on existing risk management programs as weather anomalies and government-funded disaster payouts are expected to increase in the future (Bundy et al., 2022; Reyes & Elias, 2019; Shirzaei et al., 2021; Tack et al., 2018). Thus, incorporating the loss mitigating benefits into the benefit cost analysis would provide a more comprehensive assessment of PES programs.

Finally, the findings indicate that the existing disparity between the federal crop insurance premium rate and the actual production risk could potentially be reduced by incorporating information from federal conservation programs into crop insurance premium ratings (Woodard et al., 2012; Woodard & Verteramo-Chiu, 2017). For instance, several Midwestern states (Iowa, Indiana, and Illinois) offer insurance premium discounts for cropland planted with cover crops before the subsequent cash crop season. Based on the results of this study, similar premium discounts could be considered for streambank protection and wetlands restoration practices.

2. BACKGROUND AND INSTITUTIONAL CONTEXT

2.1 Flood Risk Management: Grey and Green Infrastructure

Flooding is one of the most devastating natural disasters, with global economic losses exceeding \$1.6 trillion since 2000, making it the second costliest peril after tropical cyclones (Aon, 2023). In the United States, annualized flood losses are estimated to be \$32.1 billion under climate conditions in 2020 and are projected to rise to \$40.6 billion by 2050 under RCP4.5 scenario (Wing et al., 2022). In 2019 floods in the Mississippi River Basin prevented 20 million acres of crops from being planted, leading to approximately a \$9 billion loss in crop sales along with additional insurance indemnity payouts (English et al., 2021). These events underscore the importance of effectively managing flood risks in the era of climate change.

To mitigate flood risk, the U.S. government has primarily invested in "grey" infrastructure such as levees and dams managed by the U.S. Army Corps of Engineers (USACE), especially in the Mississippi River Basin (Bradt & Aldy, 2022; Carter et al., 2019; Galloway, 1995). Constructing levees in upstream areas, however, may displace the force of floodwaters downstream, causing negative spillover effects and increasing the cost of managing flood risk (Wang, 2021). Alternatively, "green" infrastructure, such as riparian buffers and wetlands, can provide natural solutions for flood risk management. Riparian buffers are natural vegetation planted along water bodies, while wetlands are transitional areas between land and water with distinct ecosystems. In addition to their environmental benefits, such as carbon sequestration, reduction of water pollution, and preservation of wildlife habitat, they also slow down floodwaters, reduce peak flows, and shorten flood durations, thereby mitigating flood risks for adjacent cropland (Acreman & Holden, 2013; Kousky et al., 2013; Kousky & Walls, 2014; Mason-McLean, 2020; Spalding et al., 2014).

2.2 Payments for Ecosystem Services Program

The voluntary adoption of conservation practices, however, has been limited due to several reasons (see Prokopy et al. (2019) for reviews). First, landowners may be less aware of the private benefits of adopting conservation practices because existing empirical evidence primarily emphasizes off-site public environmental benefits, rather than on-site private benefits. Second, landowners and farmers bear upfront costs to adopt conservation practices while the private benefits, such as stream bank protection and flood mitigation, are often uncertain and realized over a long-term period.

Lastly, the heavily subsidized crop insurance program in the U.S. reduces the private costs associated with production risks, potentially discouraging insured farmers from implementing long-term loss mitigation strategies (Annan & Schlenker, 2015; Claassen et al., 2017; Connor et al., 2021; Di Falco et al., 2014).

To promote the voluntary adoption of conservation practices, PES programs have been widely implemented in the U.S. and globally, aiming to establish sustainable and climate-smart agriculture. These programs offer medium- to long-term contracts (5-30 years) with financial incentives in return for adopting conservation practices, such as forest restoration, riparian buffer establishment, wetland conservation, conservation tillage, and cover cropping. Examples of existing PES programs include Conservation Reserve (Enhancement) Program (CRP and CREP) and Environmental Quality Incentive Program (EQIP) in the U.S., Agri-Environmental Schemes in the EU, Environmental Stewardship program in UK, Pagos por Servicios Ambientales (PSA) program in Costa Rica, Program of Payments for Environmental Services (PSAB) in Mexico, and Sloping Land Conversion Program (Grain for Green Project) in China.

Financial incentives within PES programs typically involve an initial payment to support the installation of conservation practices, as well as a series of annual payments to compensate for the maintenance and opportunity costs associated with practice adoption. Although participants have the option to terminate the signed contract and remove the installed practices before the contract expiration date, premature contract termination usually incurs a non-completion penalty, which often involves repayment of all or a portion of the payments received up to the time of termination.

2.3 Conservation Reserve Enhancement Program

CREP is administered by the USDA's FSA in collaboration with the USDA's Natural Resources Conservation Service (NRCS) and funded by the Commodity Credit Corporation (CCC) through partnerships with local, state, and federal governments. The primary objective of CREP is to incentivize farmers and landowners to adopt conservation practices on agricultural land to address environmental and resource concerns at the regional and national levels.[1] For example, CREP in the Mississippi River Basin aims to restore filter strips, riparian buffers, and wetlands in the major

[1] Allen (2005) noted that "CREP addresses environmental issues on the farmed landscape with implications for environmental quality potentially reaching thousands of miles away from where program conservation practices are established."

tributaries of Mississippi River (e.g., IA, IL, MN, and OH) to reduce agricultural nonpoint source water pollution in the Gulf of Mexico and preserve wildlife habitat.

The introduction of CREP in a specific county or watershed requires collaboration between the partners (local and state government) and the federal government. The partners or the federal government identify the environmental and resource concerns that can be addressed through CREP. The federal agency then reviews and evaluates proposed conservation practices and their impacts on the local community in accordance with the requirements of the National Environmental Policy Act (NEPA). The partners typically share at least 30 percent of the program costs, which can be in the form of cash, in-kind contributions, or technical assistance.

When CREP becomes available in a county, landowners with eligible agricultural land can enroll in the program on a first-come, first-served basis until the acreage goal is reached or the budget is exhausted. To be eligible for CREP, the agricultural land must be located within the project area that addresses specific environmental and resource concerns. By enrolling in the program, landowners can restore filter strips, riparian buffers, and wetlands on their eligible land in exchange for program payments. To qualify as cropland, the land must be environmentally sensitive (e.g., highly erodible) and meet specific cropping history criteria (e.g., 4 years of crop production out of the past 6 years) and be legally and physically capable of being cropped in a normal manner, which likely excludes cropland with a high risk of loss.

CREP provides financial incentives to participants to encourage the adoption of conservation practice, including both one-time upfront payments and fixed annual payments throughout the contract lifetime. For the installation of conservation practices, CREP offers cost-share assistance that covers 50 to 100 percent of the installation costs. In addition, participants receive fixed annual payments to compensate for the opportunity costs associated with land use and the maintenance costs of the installed practices. These annual program payments are designed to be competitive compared to the local soil rental rate, typically ranging from 150 to 300 percent of that rate. The payment rates are adjusted based on factors such as soil types and productivity, which are determined using the national commodity crop productivity index published by the USDA's NRCS. Some states also offer upfront signing incentive payments to further incentivize landowners to adopt conservation practices.

Because the provision of ecosystem services often depends on the growth of vegetation over time, CREP contracts typically last 10 to 15 years, with options to maintain the installed practices beyond the contract's expiration in return for additional payments. Participants have the option to terminate their contracts before the expiration date and remove the installed conservation practices. In such cases, they are obligated to repay the total payment they have received up until the termination date, along with applicable interest, as penalties for failing to complete the contract.

From its inception in year 1998 to 2022, CREP has been introduced in 32 states. In the fiscal year of 2022, CREP allocated $154 million in annual payments (excluding cost-share and signing bonus payments) to establish and maintain approximately 800,000 acres of conservation practices on agricultural land.[2]

2.4 Crop Loss Covered under the Federal Crop Insurance Program

In addition to agricultural conservation, the federal government also heavily subsidizes crop insurance program to help farmers manage risks associated with crop yield and revenue losses caused by various perils such as drought, flood, and declining crop prices. Most crop insurance plans establish either guaranteed yield or revenue by using approved Actual Production History (APH), which reflects the production potential using actual average per-acre yield of the insured's cropland for the past four to ten consecutive years (Rosch, 2021).

In the event of yield or revenue losses covered by the insurance plan, farmers receive indemnity payments from the crop insurance company as monetary compensation. These payments are calculated using projected and harvest prices obtained from the futures market. For yield protection, the guaranteed yield is determined by multiplying the APH by the selected coverage level, which can range from 50 to 85 percent with increments of 5 percent. An indemnity payment is triggered when the actual yield falls below the guaranteed yield. The indemnity payment covers the difference in yield multiplied by the selected percentage of the projected crop price. In the case of revenue protection, the guaranteed revenue is calculated by multiplying the APH, coverage level of yield, and the greater of either the projected or harvest price. An indemnity payment is triggered when the actual revenue with harvest price falls below the guaranteed revenue, and the payment compensates for the difference in revenue.

The percentage of insured U.S. cropland has constantly increased from less than 30 percent in 1989 to approximately 70 percent in 1995 and then to nearly 90 percent (299 million acres) in

[2] Program statistics are available at USDA's FSA website: https://www.fsa.usda.gov/programs-and-services/conservation-programs/reports-and-statistics/conservation-reserve-program-statistics/index.

2015 (Farrin et al., 2016; Rosch, 2021). On average, from 2000 to 2021, 82 percent of eligible acres of row crops, such as corn, soybeans, wheat, cotton, rice, sorghum, and others, were enrolled in the federal crop insurance program.[3] The coverage level of insurance, the ratio of insured liability to total potential liability, has also increased over time, reaching 74 percent by 2021. The Federal Crop Insurance Corporation provides subsidies for crop insurance premiums, ranging from 38 to 80 percent, depending on the contract terms, such as crop type, the coverage level, and an insurance unit to which the coverage level is applied to.

In the fiscal year of 2019 alone, farmers with insured cropland paid approximately $4 billion in insurance premiums while receiving nearly $8 billion of indemnity payouts (Rosch, 2021). Existing analysis of insured crop losses in the U.S. shows that nearly 2,000 counties reported crop loss in at least one crop year during 1989-2020, resulting in total indemnity payouts of $43 billion (Bundy et al., 2022). The majority of these indemnity payments (83 percent) were attributed to climate-related losses during the period from 2001 to 2016 (Reyes et al., 2020; Reyes & Elias, 2019). Crop damages caused by a water deficit or surplus, such as drought, excessive precipitation, or floods, accounted for a significant portion of these losses. Specifically, crop losses due to water surplus were concentrated in the Mississippi River Basin during the early growing season from April to July (Bundy et al., 2022).

3. DATA

I focus on agricultural counties that cultivate major cash crops in the presence of flood risk. The study sample includes counties located in the Mississippi River Basin, a region renowned for its extensive cash crop production and vulnerability to flooding because of its proximity to major tributaries of Mississippi River, such as the Missouri River, Ohio River, and Arkansas River. Data for this study is collected from the USDA's FSA and RMA, providing county-by-year panel data on flooded crop loss and the availability of CREP from 1989 to 2022. The sample dataset includes 243 counties with CREP availability across 11 states and 141 counties without CREP across 12 states in the Upper and Lower Mississippi River regions. Overall, the sample consists of counties that are actively engaged in crop production in the presence of flood risk prior to the initial introduction of CREP in the entire sample region.

[3] Overall crop insurance program statistics are available at: https://www.ers.usda.gov/topics/farm-practices-management/risk-management/crop-insurance-at-a-glance/.

A county-level analysis provides several advantages when assessing the impact of the PES program on crop loss. First, the introduction of PES programs likely alters regional landscape through restoration of riparian buffers and wetlands. Analyzing flood damage at the field or farm level may introduce potential spillover effects from surrounding land use changes, whereas a county-level analysis helps mitigate these intra-county spillover effects. Second, flooding events on cropland are typically driven by regional weather shocks, affecting multiple fields or farms within a specific area. As a result, crop losses are more likely to be regional in nature rather than specific to individual fields or farms. Lastly, conducting a county-level analysis allows for broader spatial and temporal scope of the study, covering major crop production regions in the United States over the past 34 years.

Table 1 and Figure 1 provide an overview of spatial and temporal variation in the introduction participation of CREP across the sample counties. Figure 2 illustrates the average number of acres enrolled in the CREP by practice type and the corresponding program payments in counties with CREP by the duration of program availability. To measure the extent of flood damage to crops in the sample counties, I use total indemnity payouts per flooded crop acre as the main outcome of interest. Figure 3 compares trends in average indemnity payouts per flooded crop acre between counties with and without CREP availability. Table 2 provides summary statistics for the variables used in the main analysis.

In the following subsections, I provide detail information about the county-level data on CREP availability and participation (Section 3.1), flooded crop loss covered under the federal crop insurance program (Section 3.2), and weather conditions that are used as covariates in the estimation (Section 3.3).

3.1 Conservation Reserve Enhancement Program

I focus on CREP in two Farm Resource Regions: Heartland and Mississippi River Portal, defined by the USDA's Economic Research Service (ERS) based on similar agricultural production practices, soil types, and climate conditions.[4] Both regions play a significant role in producing major cash crops, such as corn, soybeans, wheat, cotton, and rice in the U.S., in the presence of flood risk. USDA's FSA provides county-level data on the availability and participation of CREP

[4] See Farm Resource Regions defined by USDA's ERS: https://www.ers.usda.gov/publications/pub-details/?pubid=42299.

from 1998 to 2022. A county becomes CREP-available when program-eligible landowners have the opportunity to receive payments in exchange for establishing or maintaining conservation practices. County participation in CREP occurs when program-eligible landowners choose to enroll their land in the program and commit to adopting and maintaining conservation practices as specified in their CREP contract. The first year of CREP introduction may differ from the year of participation, as landowners may not enroll any acres as soon as the program becomes available. The analysis follows the fiscal year cycle of annual CREP data. For instance, the fiscal year 1998 encompasses the period from October 1997 to September 1998. This means that if CREP is introduced in the fiscal year of 1998, the conservation practices installed via CREP may provide protection services to neighboring cropland starting in the subsequent crop year of 1998. Therefore, I match crop loss information in crop year of 1998 with CREP information in the fiscal year of 1998 to construct the county-by-year panel data set.

The sample comprises (i) 243 counties from 11 states that implemented CREP by 2011 and (ii) 141 counties from 12 states that did not introduce CREP by 2011 (Table 1). CREP availability varies spatially and temporally within the same state as the partnership may prioritize a specific watershed region to address regional or national environmental concerns and then subsequently expand program availability to other regions with similar or different environmental and resource concerns. For instance, in 2005 (FY 2006) Indiana State Department of Agriculture (ISDA) partnered with USDA's FSA and introduced CREP to counties in three watersheds to reduce agricultural nonpoint source pollution and restore wildlife habitats through restoration of riparian buffers and wetlands. In 2010 (FY 2011), Indiana expanded CREP to counties located in eight other watersheds in the state with similar environmental concerns. CREP participation varies spatially and temporally across counties, even if the timing of CREP introduction is the same. For instance, the opportunity costs of program enrollment (the adoption of durable conservation measures) may vary across farms and crop year. Other factors, such as net crop return of program eligible agricultural land, crop market conditions, land ownership, age, risk preference, and education, can also influence the landowner's decision to participate in CREP (Lichtenberg, 2004, 2007; Lynch & Brown, 2000; Prokopy et al., 2019).

Figure 2 presents trends in average acres of established conservation practice and program payments since the introduction of CREP to 243 counties. During the first 11 years of the CREP implementation, the government invested a total of $440 million to establish and maintain 280,000 acres of conservation practices. Types of conservation practices installed are consistent with two main objectives of the CREP in the Mississippi River Basin: (i) reduction of agricultural nonpoint source water pollution in the Gulf of Mexico and (ii) preservation of wildlife habitat. Roughly 50 percent of total acres of conservation practices installed through CREP are riparian buffers, wetlands, filter strips, and bottomland tree planting. Likewise, restoration of wildlife habitat via vegetative buffers and conservation cover also accounts for 32 percent of total enrolled acres. The remainder of the conservation practices installed include grass and tree plantings. According to USDA's NRCS Conservation Practice Physical Effects (CPPE) and scientific literature, these conservation practices directly and indirectly mitigate flood risk by enhancing streambanks and addressing seasonal high water, ponding, and flooding (Acreman & Holden, 2013; Darby, 1999; Mason-McLean, 2020; Spalding et al., 2014).

There are two caveats in interpreting the program enrollment data. First, the program payment data only includes annual payments and does not account for one-time upfront payments, such as cost-share payments, understating the total program cost. Second, the number of enrolled acres in the program accumulates over time, including both newly enrolled acres and existing acres that receive annual payment, while excluding expired acres. To avoid (i) understating total acres of conservation practices newly installed through CREP and (ii) reversibility of program introduction, my analysis focuses on the first 11 years of program availability, including the year of program introduction, as most CREP contracts last for at least a decade.

In the setting of staggered policy rollout, panel data sets that are balanced in calendar time become unbalanced in event time (duration after the policy onset) due to variations in the timing of policy adoption across counties.[5] This implies that the estimated program effect across event time may vary simply due to changes in the composition of treated counties. To address this concern, the analysis sample consists of counties with at least 11 years of exposure to the program availability, including the year of program introduction (Figure 1).

3.2 Flooded Crop Loss

The Cause of Loss data from USDA's RMA provide detailed information on county-by-month crop loss covered under the federal crop insurance program, categorized by crop type and cause of

[5] Likewise, each treated county has different number of pre-policy periods, from minimum 9 years for those treated in 1998 to maximum 22 years for those treated in 2011.

loss, from 1989 to 2022. Flooded crop loss may vary spatially and temporally depending on geographical conditions, hydrological networks, and weather conditions, such as excessive precipitation. To measure the extent of crop damage due to flooding, I use the ratio of total indemnity payouts for flooded crop damage to the total number of flooded crop acres reported in the federal crop insurance program. I also use indemnity payouts per liability (loss cost) or insured acre as robustness checks. These measures of crop loss have been extensively used in the analysis of crop losses and actuarial assessments of the federal crop insurance program (Bundy et al., 2022; Changnon & Hewings, 2001; Coble & Barnett, 2013; Glauber, 2004; Reyes et al., 2020; Reyes & Elias, 2019; Woodard et al., 2011, 2012). I aggregate the flooded crop loss to the county-by-year level, including all insurance plans with coverage level and eight major cash crops (corn, soybeans, wheat, rice, cotton, barley, oats, and grain sorghum) in the Mississippi River Basin from 1989 to 2022. I expect indemnity payouts per flooded crop acre to decrease after the introduction of CREP if conservation practices installed through CREP attenuate regional flood risk as suggested by scientific studies.

One important caveat of measuring crop loss using federal crop insurance program data is that the recorded crop loss only captures a partial view of the actual crop loss occurring within a county. For example, no indemnified crop acres in each year may indicate at least three possible scenarios: (i) the county did not experience actual crop loss, (ii) the county had no insured crop acres regardless of the extent of actual crop loss on uninsured acres, or (iii) the county experienced crop loss that is not large enough to trigger any indemnity payouts from the crop insurance program. These limitations have implications for estimating the causal impact of PES program on crop loss. For instance, reductions in flood damage observed in CREP-available counties may be attributed to relatively lower crop insurance adoption compared to comparison counties, thus overstating program's impact on crop loss.

To mitigate this concern, I use the Summary of Business data from USDA's RMA to focus my analysis on counties with insured crop acreage for the same eight major cash crops in the loss data set throughout the entire sample period.[6] In addition, I compare the extent of crop insurance adoption between CREP-available counties and control counties, using both total number of acres insured and selected coverage levels, during the pre- and post-program periods. Finally, I focus

[6] On average, 82 percent of eligible row crop acres in the U.S. are insured from 2000 to 2021, according to USDA-ERS (Section 2.4).

on counties that experienced actual flooded crop loss covered under the federal crop insurance program before the first introduction of CREP in the U.S. in 1998.

Figure 3 shows trends in flooded crop losses, measured by indemnity payouts per flooded crop acre, in counties with and without CREP. Flooded crop losses are large in the years of major flood events in the Mississippi River Basin such as the years of 2008, 2011, and 2019. On the other hand, flooded crop losses are small in the year of severe drought such as the year of 2012. Overall, flooded crop loss covered under the federal crop insurance program has been increasing due to the increased extent of weather anomalies and the extent of crop insurance adoption (e.g., coverage level). Counties with CREP on average have lower flooded crop loss after the first program introduction in the U.S. in 1998 compared to non-CREP counties while this observed divergence may not necessarily be attributed to the CREP in the presence of unobserved heterogeneity and time-varying confounding factors, such as potential divergence in weather and production conditions, crop insurance adoption, and participation in other similar conservation programs. I directly compare trends of these observable confounding factors between CREP and non-CREP counties as robustness checks in the result section.

3.3 Weather

Climate conditions during the post-harvest (October to March) and growing seasons (April to September) affect future crop insurance decision and crop productivity (Moore & Huang, 2019). To ensure that the treated and control counties share similar climate conditions, I include county-by-year (i) precipitation (mm) and (ii) growing degree days in both post-harvest and growing seasons (total four) as auxiliary covariates in the estimation of program effect. These weather variables are constructed based on grid-cell level (2.5 by 2.5 mile) daily temperature data from the PRISM (Parameter-elevation Regressions on Independent Slopes Model) Climate Group (Schlenker & Roberts, 2009). Growing degree days represent the accumulated temperature between 10 and 29 degrees Celsius, which is a more accurate measure for explaining variations in crop yield compared to average temperature (Auffhammer & Schlenker, 2014; Carleton & Hsiang, 2016). I use average values of precipitation and growing degree days observed during post-harvest season (October to March) and crop growing season (April to September) from fiscal years 1989 to 1997 (Table 2).

4. EMPIRICAL FRAMEWORK

I now provide an overview of the empirical methodology employed to estimate the causal impact of CREP introduction on flooded crop loss. The estimand of interest is the average treatment effect on the treated (ATT), which measures the average impact of CREP introduction on flooded crop loss for counties where CREP is available. To estimate the ATT, I employ the SCM with an intercept shift adapted to the setting of staggered policy rollout across multiple treated units. In the following subsections, I first introduce the notation and define the estimand of interest for the empirical analysis. Then, I discuss the identification strategy and the validity of identification assumptions to provide an intuitive understanding of the approach. Lastly, I describe the partially pooled SCM with additional information available in Appendix A.

4.1 Estimands of Interest

One ideal experiment to assess the loss mitigation benefits of CREP using a DID approach would be comparing trends in flooded crop losses between two groups of counties that are identical in all aspects except for the introduction of CREP at a certain point in time. Before the introduction of CREP, both groups of counties would have the same trajectories of crop loss due to the shared determinants of crop loss such as inherent flood risk and trends in weather conditions. However, after the introduction of CREP in one group of counties, any divergence in flooded crop loss between the two groups would be attributed to the program's effect, providing insights into the dynamic impact of CREP on mitigating crop loss. In this experiment, the group of counties without CREP serves as a credible comparison unit, representing what the counties with CREP would have experienced in the absence of the program. Thus, by examining the differential changes in flooded crop losses over time, one can estimate the loss mitigation benefits attributable to CREP.

Suppose that I observe annual crop loss for $i = 1, \dots, N$ counties over $t = 1, \dots, T$ years with variation in timing of program introduction across counties. Let T_i denote the first year of PES program introduction to a county i (i.e., the first year of county being "treated"). Without loss of generality, assume that $T_1 \leq T_2 \leq \cdots \leq T_N$. Let $j = 1, \dots, J$ denote the treated counties where PES program was eventually available by year T. An event time $k \leq K$ is the year relative to the first year of CREP availability T_j $\left(k = t - T_j\right)$. For each treated county j, we observe $L_j (\leq T_j - 1)$ pre-policy outcomes with $L \equiv max_{j \leq J} L_j$. Let N_0 denote the number of counties where the PES program was not available during the sample period with $T_i = \infty$ denoting that the county is never treated, then $J = N - N_0$. Using the potential outcomes framework (Rubin, 1974), let Y_{it} denote the observed crop loss in county i in year t and $Y_{it}(s)$ denote the potential outcome when PES program first becomes available in county i in year $s = 1, \ldots, T, \infty$. Under no policy anticipation effect and stable unit treatment value assumption (SUTVA), the observed crop loss outcome is then $Y_{it} = \mathbb{1}\{t < T_i\} Y_{it}(\infty) + \mathbb{1}\{t \geq T_i\} Y_{it}(T_i)$ where $Y_{it}(s) = Y_{it}(\infty)$ for $t < s$.

I expect that the loss mitigation benefits of PES program would generally increase with the duration of program availability (event time) due to two main factors: (i) program participation to establish conservation practices increases over time and (ii) the effectiveness of established conservation practices improves over time as vegetation on riparian buffers and wetlands matures over time. Consider the evolution of crop loss experience in a county j treated in year T_j across event time k relative to its average crop loss outcome during L_j pre-policy periods (i.e., the trajectory of treated outcome):

$$\dot{Y}_{jT_j+k}(T_j) \equiv Y_{jT_j+k}(T_j) - \frac{1}{L_j}\sum_{l=1}^{L_j} Y_{jT_j-l}\,. \tag{1}$$

Then, for the same county, the counterfactual evolution of crop loss outcome from its pre-policy average to time $T_j + k$ is $\dot{Y}_{jT_j+k}(\infty)$, that is, the counterfactual trajectory of post-policy crop loss had the policy not introduced to county j in year T_j.

A county-specific program effect at event time k for each county j treated in year T_j is then:

$$\tau_{jk} = \dot{Y}_{jT_j+k}(T_j) - \dot{Y}_{jT_j+k}(\infty), \tag{2}$$

where $\tau_{jk} = 0$ for any $k < 0$ in the absence of policy anticipation and spillover effects. Then, the average effect of PES program availability on the treated counties, $k \geq 0$ years after the program onset (ATT_k) is:

$$ATT_k \equiv \frac{1}{J}\sum_{j=1}^{J} \tau_{jk} = \frac{1}{J}\sum_{j=1}^{J}\left[\dot{Y}_{jT_j+k}(T_j) - \dot{Y}_{jT_j+k}(\infty)\right]. \tag{3}$$

Lastly, the overall impact of the introduced policy across event time k is:

$$ATT \equiv \frac{1}{K+1}\sum_{k=0}^{K}\frac{1}{J}\sum_{j=1}^{J}\tau_{jk}\,. \tag{4}$$

4.2 Identification Strategy

My identification strategy encounters two main empirical challenges. First, the availability of CREP across the sample counties may be driven by factors that also drive flood damage on cropland. For example, counties located in high flood risk watersheds tend to transport nutrients and sediment from cropland to water bodies, resulting in the implementation of CREP to address water quality concerns through nature-based infrastructure. Second, the staggered rollout of CREP and the program effect heterogeneity across counties require careful selection of a comparison group to avoid bias in the estimated program effect (Baker et al., 2022; Borusyak et al., 2021; Goodman-Bacon, 2021; Roth et al., 2023).

CREP in the Mississippi River Basin provides a unique opportunity to evaluate how conservation investments made through PES program mitigate crop damage under extreme weather events for several reasons. First, the introduction of CREP in counties of the Mississippi River Basin is mainly driven by the partnership between the state and the federal governments, aiming to address environmental concerns on agricultural nonpoint source water pollution in the Gulf of Mexico and declining of wildlife habitat, rather than an individual county's indemnity receipts due to crop loss, which mitigates the concern of reverse causality. Second, the staggered rollout of CREP across counties within the same state allows for suitable comparison group of counties because they have similar unobserved confounding factors, such as crop type, farming practice, production and climate conditions, and state-level land use policies. Third, farmers have little incentive to manipulate or adjust their reported crop losses in anticipation of the new PES program, which mitigates the potential anticipation effect on crop loss. Lastly, the introduction of CREP likely leads to a medium- to long-term change in the regional landscape through the restoration of riparian buffers and wetlands, which implies a strong first stage impact assuming high additionality of the program.[7]

[7] Existing theoretical and empirical studies suggest imperfect additionality of PES program, which implies that farmers and landowners would have adopted conservation practices even in the absence of the financial incentives offered by PES program (Chambers, 1992; Ferraro, 2008; Ferraro & Simpson, 2002; Fleming, 2017; Fleming et al., 2018; Lichtenberg, 2021; Lichtenberg & Smith-Ramirez, 2011; Mezzatesta et al., 2013; Wu & Babcock, 1996). Thus, the introduction of PES program with little additionality would not increase overall conservation practice adoption. Additionality of the U.S. federal PES programs is typically higher for land use conversion practices, such as restoration of riparian buffers and filter strips in CRP (96-98 percent), compared to working land practices, such as conservation tillage in EQIP (47 percent) (Claassen et al., 2018).

To estimate the average crop loss that counties with CREP (treated) would have experienced in the absence of the program, neither a single county nor all counties without CREP (untreated) may serve as a valid comparison group. Instead, I employ synthetic control method, which uses a weighted combination of untreated counties that had similar crop loss experience during the pre-policy periods to estimate the counterfactual crop loss of the treated. SCM has been widely used in the existing literature to estimate the causal impact of policy implementation on single or multiple units (Abadie, 2021; Abadie et al., 2010, 2015; Abadie & Gardeazabal, 2003; Acemoglu et al., 2016; Kreif et al., 2016; Robbins et al., 2017). In this analysis, I employ partially pooled SCM that accounts for multiple treated units in the setting of staggered policy rollout (Ben-Michael et al., 2022). To account for differences in the level of crop loss across the sample counties, I include an intercept shift in constructing synthetic controls for treated counties (Doudchenko & Imbens, 2016; Ferman & Pinto, 2021).

The resulting treatment effect estimator takes the form of a weighted DID estimator, where the weights for untreated counties are non-uniform, sparse, and chosen to maximize the similarity between the synthetic control counties and the treated counties in terms of both *individual* and *average* pre-policy trends in crop loss. Key identification assumptions of the partially pooled SCM generally align with those of DID estimator, including the absence of time-varying confounding factors, policy anticipation effects, and spillover effects (i.e., SUTVA). This estimator addresses identification challenges that arise from potential program effect heterogeneity and timing variation in program introduction as other weighted DID estimators in the literature do (Callaway & Sant'Anna, 2021; de Chaisemartin & d'Haultfoeuille, 2020; Sun & Abraham, 2021).

Time-varying confounding factors pose a threat to identification because the divergence in post-policy crop loss between counties with CREP and synthetic controls could be attributed to factors other than the introduction of CREP. For instance, simultaneous increases in the participation of other conservation programs that support similar conservation practices in CREP-available counties may lead to an overestimation of CREP impact on crop loss. Similarly, a decrease in crop insurance adoption in CREP-available counties at the time of CREP introduction could decrease overall reported crop losses, thus overstating the program's effect. Lastly, a decrease in weather risk, such as excessive precipitation, in CREP-available counties during the post-policy period could also overstate the program's effect. Although the assumption of no time-varying confounding factors is fundamentally untestable due to potential unobserved confounding factors that vary over time, I examine the parallel pre- and post-trend of observed time-varying confounding factors, such as conservation practice adoption from other similar conservation programs, crop insurance adoption, and weather conditions, to enhance the credibility of the estimated program effect.

The assumption of no policy anticipation effect is plausible because the availability of CREP in each county is primarily driven by the partnership between the state and federal governments to address environmental quality concerns that extend across vast distances, such as nutrient pollution in the Gulf of Mexico (see Allen (2005) and section 2.3 for details). Thus, individual landowners may not be aware of future program availability or do not have incentive to manipulate crop loss in anticipation of program introduction. In addition, landowners make conservation decisions for agricultural land, while tenant farmers make decisions on crop production and insurance, mitigating the potential anticipation effect on crop insurance and cropping decisions of rented farms.[8]

Suppose that conservation practices implemented through CREP effectively reduce flooded crop losses. The assumption of no spillover effects is plausible if the flood mitigation benefits of these practices diminish with increasing distance and primarily benefit farms within the same county. Spillover effects between counties, however, can bias the estimated program impact (a) downward if flood mitigation practices in upstream counties with CREP also reduce flooded crop loss in downstream non-CREP counties that contribute to synthetic control group, or (b) upward if flood mitigation practices in upstream counties with CREP further reduces flooded crop loss in downstream counties with CREP. However, unless the composition of neighboring upstream county and the magnitude of spillover effects between neighboring counties are systematically associated with CREP availability, the estimated average program effect on flooded crop loss in counties with CREP would not be significantly biased by spillover effects.

4.3 Partially Pooled Synthetic Control Method

The estimation of the average program effect on crop loss in treated counties, as described in equations (3)-(4), involves estimating the counterfactual trajectory of average crop loss in the treated counties during the post-policy periods. Unlike the synthetic control method that typically

[8] In the U.S., cash grains, including rice, corn, soybeans, wheat, and cotton, are cultivated in regions where more than 50 percent of farmland is leased or rented (Bigelow et al., 2016).

has a single treated unit, in this study, multiple synthetic controls are constructed for each treated county $j = 1, \ldots, J$. Partially pooled SCM with an intercept shift estimates the counterfactual trajectory of average crop loss in the treated group by allocating weights across untreated counties to maximize the similarity between the synthetic control counties and the treated counties in terms of both *individual* and *average* pre-policy trends in crop loss (Ben-Michael et al., 2022; Doudchenko & Imbens, 2016; Ferman & Pinto, 2021). In detail, the partially pooled SCM minimizes the weighted average of two imbalance measures, motivated by the two different interpretations of ATT_k in equation (3): (i) the average of difference in pre-policy trends in outcomes between the treated and synthetic control counties (individual fit) and (ii) the difference in average pre-policy trends in outcomes between the treated and synthetic control counties (pooled fit).

The resulting estimator takes the form of a weighted DID estimator $\hat{\tau}_{jk}$:

$$\hat{\tau}_{jk} = \dot{Y}_{jT_j+k}(T_j) - \hat{\dot{Y}}_{jT_j+k}(\infty) \tag{5}$$
$$= \left[Y_{jT_j+k}(T_j) - \frac{1}{L_j}\sum_{l=1}^{L_j} Y_{jT_j-l} \right] - \left[\sum_{i=1,\neq j}^{N} \hat{\gamma}_{ij}\, Y_{iT_j+k} - \frac{1}{L_j}\sum_{l=1}^{L_j}\sum_{i=1,\neq j}^{N} \hat{\gamma}_{ij}\, Y_{iT_j-l} \right],$$

where weights for untreated counties $\hat{\gamma}_{ij}$ are chosen to minimize imbalance of both individual and average pre-policy trends in crop loss (see Appendix A for derivation). The estimated county-by-event time treatment effect $\hat{\tau}_{jk}$ can be aggregated to obtain estimated average program effect on the treated county $\widehat{ATT_k}$ and the overall treatment effect $\widehat{ATT}$ using equations (3) and (4). This estimator addresses unobserved heterogeneity across counties and allows for program effect heterogeneity and staggered program adoption, while it differently assigns weights to untreated counties compared to other DID estimators proposed by Callaway & Sant'Anna (2021) and Sun & Abraham (2021). The estimator is also similar to the synthetic DID estimator proposed by Arkhangelsky et al. (2021) but is extended to multiple treated units without time weighting. For statistical inference, I use wild bootstrap to construct confidence intervals around the estimated ATT following Ben-Michael et al. (2022).[9]

In addition to lagged outcomes, I include average total precipitation and growing degree days in post-harvest season (October to March) and crop growing season (April to September) from

[9] See also Cao & Lu (2019) and Cattaneo et al. (2022) that examine inference for SCM-type estimators in the setting of staggered policy rollout.

1989 to 1997 as auxiliary covariates in choosing synthetic control weights for untreated counties. Historical weather conditions may capture additional information that explains future crop loss that cannot be fully explained by pre-policy crop loss experience. For example, characteristics of farms in the county, such as crop type, crop profitability, and farming practices, are likely to be similar across counties that have similar historical weather conditions as well as parallel pre-policy trends in crop loss. Thus, including climate conditions to choose weights for donor counties likely generate synthetic control counties that consist of qualitatively similar farms compared to the treated counties, except the availability of CREP. As a robustness check, I also present the result excluding auxiliary covariates.

The synthetic control counties used in the estimation consists of untreated counties that are geographically closer to the counties with CREP (Figure 4). In the analysis of crop loss covered under the federal crop insurance program, counties that are geographically proximate to each other tend to exhibit similarities in production conditions, farm characteristics, crop type and insurance decision, and other determinants of current and future crop loss. For example, in Iowa, 35 counties with CREP have a total of 35 synthetic controls that primarily consist of donor counties within the same state (67 percent) and neighboring state, South Dakota (20 percent), on average. Each synthetic control county typically consists of 5 to 11 different untreated counties with an average of 7.9 counties. Overall, the post-policy average counterfactual crop loss of counties with CREP is estimated based on the post-policy average crop loss of multiple neighboring untreated counties that exhibit parallel pre-policy trends in crop loss and similar production conditions.

5. RESULTS

I first present the estimated overall flood mitigation benefits of the CREP during the initial 11 years of program implementation as shown in equations (3) and (4). Then, I examine potential confounding factors that could influence the estimated program effects. Additionally, I conduct a falsification test that examines the effects of CREP on outcomes that are not expected to be influenced by the program. Finally, I discuss the robustness of the results, exploring different outcomes measures and sensitivity checks in the estimation of program effects.

5.1 PES Program Effects on Flood Damage

I find economically and statistically significant flood mitigation benefits of conservation investments made through CREP (Figure 5). Before the introduction of CREP, both counties with CREP and the synthetic control group exhibit parallel trends in average crop loss with a small difference in level. After the introduction of CREP, however, the two groups experienced divergence in flooded crop loss (Figure 6). The average indemnity payouts per flooded crop acre in counties with CREP is only $1/acre lower than that in the synthetic controls during the pre-policy periods, but the gap increases to $23/acre during the post-policy periods. Thus, in the first 11 years of CREP implementation, the estimated average reduction in indemnity payouts per acre loss is $22/acre, which corresponds to a 27 percent decrease from the estimated counterfactual crop loss, that is, the sum of average post-policy outcome in synthetic controls ($82/acre) and pre-policy difference in average outcome (-$1/acre). The flood mitigation benefits generally increase with the duration of program availability. On average, the reduction in indemnity payouts per flooded crop acre rises from $13/acre (21 percent) during the first 5 years to $30/acre (30 percent) after 6 to 11 years of program implementation.

I also find that both total indemnity payouts (numerator) and crop acres lost (denominator) due to flooding in counties with CREP decreased after the introduction of CREP, compared to the synthetic control group. During the pre-policy periods, the average indemnity payouts for flooded crop damage in counties with CREP is only $2,457 lower than that of synthetic control counties ($42,062 and $44,519). The difference, however, increases to $84,992 during the post-policy periods ($69,315 and $154,307). Similarly, the average crop acres lost due to flooding in counties with CREP is only 23 acres lower than that of synthetic control counties during the pre-policy periods (409 and 432 acres), while the difference increases to 262 acres during the post-policy periods (363 and 625 acres). Combining synthetic control's post-policy average outcome and pre-policy difference in average outcome between the treated and synthetic control group, the introduction of CREP led to an average reduction of 54 percent in total indemnity payouts and a 39 percent decrease in acres lost due to flooding.

To assess the overall reduction in flooded crop loss due to the introduction of CREP counties, I combine the reduced indemnity payouts for flooded crop acres in counties with CREP ($22/acre reduction for 363 acres lost) with the avoided indemnity payouts resulting from the reduced number of flooded crop acres in these counties ($81/acre reduction for 239 acres lost). This calculation yields a total savings of $73 million in indemnity payouts due to flooding that would have been paid to the insureds in the absence of CREP across 243 counties during the first 11 years of CREP implementation. Furthermore, using the estimated counterfactual post-policy average indemnity payouts per flooded crop acre in counties with CREP ($81/acre), the total avoided flood damage due to CREP in terms of crop acres amounts to 900,000 acres.

5.2 Potential Confounding Factors

Key identification assumption of weighted DID estimators is the absence of time-varying confounding factors that may also cause the post-policy divergence in outcome other than the introduction of CREP, such as post-policy divergence in (i) crop insurance adoption, (ii) weather conditions, and (iii) conservation investments from other similar PES programs. The assumption of no time-varying confounding factor is fundamentally untestable due to unobserved confounding factors. At a minimum, I investigate whether observable time-varying confounding factors present relatively parallel pre- and post-trend to add credibility of the estimated program effect.

First, the reduced insurable crop losses in CREP counties may be attributable to a post-policy divergence in crop insurance decisions. For example, landowners in counties where CREP is implemented may lower the extent of insurance adoption, as they consider the potential reduction in flood risk resulting from the restoration of riparian vegetative buffers and wetlands. In this case, decreases in crop loss in CREP-available counties may be attributable to the lowered insurance adoption rather than the protection services of conservation practices installed via CREP. I find that both the number of insured acres and the coverage level adopted have relatively parallel pre- and post-trend (Figure B1 and B2 in Appendix B). The adoption of conservation practices may not significantly affect insurance adoption for two reasons: 1) the loss mitigation benefits of conservation practices may be uncertain to landowners, at least in the short run, as little empirical evidence currently exists except field experiments and 2) the federal crop insurance program covers loss in yield and revenue caused by multiple perils including decline in price while conservation practices may not.

Second, the post-policy divergence in crop losses between counties with CREP and synthetic control may be attributable to different weather conditions that affect flood risk such as excessive precipitation and temperature. I find that both total precipitation and growing degree days during crop growing season, April to September, have relatively parallel pre- and post-trend (Figure B3 and B4). Thus, the post-policy reduction of crop loss in counites with CREP may not be driven by differential production conditions.

Lastly, an interaction between existing conservation programs may confound the flood mitigation effect of CPEP on crop loss. For example, landowners who would have installed conservation practices on their cropland via other conservation programs (e.g., general signup or non-CREP continuous signup) may switch to enroll in CREP due to competitive financial incentives and low transaction cost. On the other hand, landowners in counties without CREP may enroll their cropland in other conservation programs to install similar conservation practices. In this case, the estimated CREP impact on flood damage is attenuated because non-CREP counties also make investments in similar conservation practices via other conservation programs. I find relatively parallel post-policy trends in conservation investments made via other similar conservation programs between counties with CREP and synthetic controls (Figure B5). Thus, the post-policy reduction of crop loss in counties with CREP may not be driven by differential conservation investments made by similar other programs.

5.3 Falsification Test

I investigate whether a placebo outcome that should not be affected by conservation investments made via CREP diverges after the introduction of CREP between counties with and without CREP. The federal crop insurance program's revenue protection covers the insured's revenue loss due to decline in projected or harvest crop price in the futures market (see Section 2.4 for details). Indemnity payouts due to decline in crop price thus serve as a placebo outcome that should not be affected by the availability of CREP. Unlike post-policy divergence in indemnity payouts due to flooding between counties with CREP and synthetic control, I do not find post-policy divergence in loss due to decline in crop price (Figure B6). This implies that the comparison between counties with CREP and the synthetic control group is expected to show differences in outcomes that are specifically related to the availability of CREP, such as the reduction in flooded crop loss.

5.4 Robustness Checks

The findings are qualitatively robust to several modifications made in the estimation of program effects. First, when only pre-policy outcomes are considered for allocating weights to donor counties that consist of synthetic control, the estimated reduction in flooded crop damage decreases slightly from 27 percent to 20 percent and is statistically significant (Figure B7). In this case, synthetic controls are untreated counties that are geographically farther away from the treated counties as weather conditions are not explicitly considered in the weight allocation process. Second, flood mitigation benefits remain persistent and statistically significant even when estimating the program effects for up to 21 years of implementation, yielding a similar 27 percent reduction in flood damage. Third, the estimated program effects are not driven by a few counties with extreme program effects during certain event times. The overall program effect is stable in magnitude even when excluding the top and bottom 1 or 5 percentile of county-by-event time program effects ($23-$24/acre reduction in indemnity payouts per flooded crop acre, compared to $22/acre in baseline). Fourth, the findings remain qualitatively similar when using different functional forms of the crop loss outcome. The estimated program effect, using inverse hyperbolic sine (IHS) transformation of the outcome to account for years with zero flooded crop loss, shows statistically significant flooded mitigation benefits with similar trajectory of benefits over time (Figure B8) (Bellemare & Wichman, 2020). Lastly, the findings are also qualitatively similar when using alternative crop loss measures such as the ratio of total indemnity payouts due to flooding to either total liability or total insured acres. Overall, the findings are robust to sensitivity checks in the estimation of program's flood mitigation benefits.

6. PROGRAM EFFECT HETEROGENEITY

The loss mitigation benefits of nature-based infrastructure established through PES programs may vary spatially and temporally across counties. To examine the program heterogeneity, I investigate the linear relationship between the estimated county-by-event time program effect on flooded crop loss, denoted as $\hat{\tau}_{jk} (0 \leq k \leq 10)$ in equation (5), and county-level characteristics that may explain the variability in loss mitigation benefits. These characteristics include the duration of exposure to CREP availability, the acreage enrolled in CREP, the presence of alternative risk management strategies, and the overall resilience of the county to natural disasters (see Table 3). In this analysis, I use 2592 out of 2673 estimated county-by-event time program effects from 243 treated counties for 11 years of post-policy event time because county-level weather data are not available in the year 2020-2021. The results of the multivariate linear regression are presented in Table 4.

6.1 Nature-based Infrastructure Established through CREP

A potential mechanism of the estimated loss mitigation benefits of PES program availability is the establishment of conservation practices subsidized by the program. I use the cumulative acreage of conservation practices established through CREP to measure the extent of natural infrastructure established in each county after the program introduction. I find that the loss mitigation benefits increase with both the duration of exposure to the PES program and the cumulative acreage of conservation practices implemented through the program (Panel A of Table 4). This confirms that the estimated loss mitigation benefits are likely driven by the adoption of flood mitigation practices on agricultural land under CREP. The duration of program availability may influence the estimated loss mitigation benefits, as it partially captures the maturity of vegetation on conservation practices installed through the program. Note that the model controls for annual weather conditions during the crop growing season at the county-level to account for spatial and temporal variations in production conditions across treated counties.

6.2 Spillover Effects

Neighboring counties are often intricately connected through hydrological networks, with water flowing both into and out of each other. Scientific studies indicate that riparian buffers and wetlands have the potential to decrease seasonal high water levels and peak flow in the region, particularly during periods of excessive precipitation. While the specific locations of conservation practices established through CREP are not provided, I explore the extent of inter-county spillover effects by examining whether the magnitude of flood mitigation benefits is influenced by the number of neighboring counties that have also implemented CREP by 2011. I find that the introduction of the program in neighboring counties does not affect the extent of loss mitigation benefits (Panel B of Table 4). This implies that the loss mitigation benefits of natural infrastructure on agricultural land are primarily confined to the cropland within the county.

6.3 Presence of Existing Infrastructure for Flood Mitigation

Levee construction along rivers and water bodies is an alternative flood risk mitigation measure in the Mississippi River Basin. If croplands are already protected from flood risk by levees, the establishment of conservation practices along water bodies may have a smaller impact compared to areas without existing flood mitigation measures. To assess the interaction between protection services provided by green and grey infrastructures (forests and wetlands versus levees), I explore a linear association between the magnitude of estimated loss mitigation benefits of PES program and the area of floodplain excluded from floodwater by levee systems, obtained from the USACE National Levee Database. I find that the estimated loss mitigation benefits of the PES program decrease with the extent of floodplain area protected by levees (Panel C of Table 4). This suggests that nature-based infrastructure installed through PES programs can serve as an alternative risk mitigation strategy in areas with limited protection from flood risk.

6.4 Farm Resource Region

Counties in the Mississippi River Portal region, located downstream of the Mississippi River Basin, have historically faced higher flood risk compared to counties in the Heartland region (Galloway, 1995). I find that the loss mitigation benefits of natural infrastructure are greater in counties with higher flood risk (Panel D of Table 4). This indicates that the implementation of PES programs can bring about significant changes in the regional landscape, effectively reducing the inherent high flood risk in these areas along with levee construction.

6.5 Crop Insurance Adoption

The magnitude of financial spillover effects to the federal crop insurance program may vary depending on the extent of crop insurance adoption in the county. For example, counties heavily reliant on crop insurance may experience a greater decrease in crop insurance claims compared to counties with low insurance adoption. I find that the loss mitigation benefits of the PES program are higher in counties with a high insurance coverage rate but lower in counties with a larger insured acreage (Panel E of Table 4). This suggests that the introduction of the PES program is likely to reduce indemnity payouts for heavily insured farmers by promoting the adoption of risk-reducing practices under extreme weather events in the era of climate change.

6.6 Community Resilience to Natural Disaster

Lastly, the magnitude of loss mitigation benefits provided by natural infrastructure may vary depending on a county's inherent vulnerability to climate change impacts. The Community Risk Factor (CRF), a county-level measure provided by the Federal Emergency Management Agency (FEMA), aims to identify communities with higher social vulnerability and lower community resilience to natural disasters. The CRF is derived from socio-economic conditions such as race, income, age, education, housing, as well as the capacity to recover from the adverse consequences of natural hazards. The CRF ranges from 0.5 to 2, with higher values indicating weaker resilience to natural disasters. I find suggestive evidence that the magnitude of loss mitigation benefits increases with CRF, although the linear association is not statistically significant (Panel F of Table 4). This implies the potential for PES programs to generate greater benefits when introduced in communities that are more vulnerable to climate risks.

7. CONCLUSION

This study examines empirically the extent to which the introduction of PES programs enhances resilience to extreme weather shocks in agriculture. The analysis focuses on the staggered rollout of the USDA's CREP across counties in the Mississippi River Basin starting in 1998, which aimed to reduce nutrient pollution in the Gulf of Mexico and restore wildlife habitat. Conservation practices established through CREP include riparian buffers and wetlands that mitigate regional flood risks as well as provide a multitude of environmental benefits. By analyzing county-level panel data on CREP availability and flooded crop losses across 384 counties from 1989 to 2022, synthetic control estimates indicate that the introduction of CREP reduced the number of flooded crop acres by 39 percent and mitigated the extent of damage on those acres by 27 percent during the initial 11 years of program implementation. Flood mitigation benefits generally increase with the duration of program availability, protecting 900,000 crop acres from flooding and saving $73 million in indemnity payouts. Lastly, the benefits vary spatially and temporally depending on the extent of program participation and the adoption of alternative risk management strategies in agriculture.

There are two caveats in interpreting the results. First, the flood mitigation benefits of this PES program, which diverts cropland out of production, may also be attributed to the removal of high-risk cropland out of production, in addition to protection services provided by conservation practices installed through the program. Second, the federal crop insurance program data exclude flood damages on uninsured cropland or relatively small crop losses that do not meet the coverage level requirements for an indemnity payout.

Global initiatives to mitigate and adapt to climate change are increasingly focused on climate-smart agriculture as a means to sequester carbon and build resilience to extreme weather events.

PES programs can play a central role in these efforts through agricultural conservation, reforestation, and avoided deforestation. This paper provides robust empirical evidence that nature-based infrastructure established through PES program may effectively mitigate crop loss and provide valuable protection against increasing weather anomalies. The results also suggest that PES programs contribute to the sustainability of existing risk management programs, such as the crop insurance program. Overall, these findings highlight the critical role of PES programs and natural infrastructure in facilitating climate change adaptation.

References

Abadie, A. (2021). Using synthetic controls: Feasibility, data requirements, and methodological aspects. *Journal of Economic Literature*, *59*(2), 391–425.

Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American Statistical Association*, *105*(490), 493–505.

Abadie, A., Diamond, A., & Hainmueller, J. (2015). Comparative politics and the synthetic control method. *American Journal of Political Science, 59*(2), 495–510.

Abadie, A., & Gardeazabal, J. (2003). The economic costs of conflict: A case study of the Basque Country. *American Economic Review*, *93*(1), 113–132.

Abadie, A., & L'Hour, J. (2021). A penalized synthetic control estimator for disaggregated data. *Journal of the American Statistical Association*, *116*(536), 1817–1834.

Acemoglu, D., Johnson, S., Kermani, A., Kwak, J., & Mitton, T. (2016). The value of connections in turbulent times: Evidence from the United States. *Journal of Financial Economics*, *121*(2), 368–391.

Acreman, M., & Holden, J. (2013). How wetlands affect floods. *Wetlands*, *33*(5), 773–786.

Alix-Garcia, J., & Wolff, H. (2014). Payment for ecosystem services from forests. *Annual Review of Resource Economics*, *6*(1), 361–380.

Allen, A.W. (2005). The Conservation Reserve Enhancement Program. USGS Staff – Published Research. 191. Available at: https://digitalcommons.unl.edu/usgsstaffpub/191

Annan, F., & Schlenker, W. (2015). Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat. *The American Economic Review: Papers and Proceedings*, *105*(5), 262–266. http://www.jstor.org/stable/43821890

Aon. (2023). *Weather, Climate and Catastrophe Insight: 2023 Annual Report.* London, UK: Aon.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G.W., & Wager, S. (2021). Synthetic difference-in-differences. *American Economic Review, 111*(12), 4088–4118.

Auffhammer, M., & Schlenker, W. (2014). Empirical studies on agricultural impacts and adaptation. *Energy Economics, 46*, 555–561.

Baker, A. C., Larcker, D. F., & Wang, C. C. Y. (2022). How much should we trust staggered difference-in-differences estimates? Journal of Financial Economics, 144(2), 370–395.

Basche, A.D., & DeLonge, M.S. (2019). Comparing infiltration rates in soils managed with conventional and alternative farming methods: A meta-analysis. *PLoS One*, *14*(9), e0215702–e0215702.

Baylis, K., Coppess, J., Gramig, B.M., & Sachdeva, P. (2022). Agri-environmental programs in the United States and Canada. *Review of Environmental Economics and Policy*, *16*(1), 0.

Bellemare, M.F., & Wichman, C.J. (2020). Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*, *82*(1), 50–61.

Ben-Michael, E., Feller, A., & Rothstein, J. (2022). Synthetic controls with staggered adoption. *Journal of the Royal Statistical Society Series B, Royal Statistical Society*, *84*(2), 351–381.

Bigelow, D., Borchers, A., & Hubbs, T. (2016). *US farmland ownership, tenure, and transfer*. Economic Information Bulletin Number 161. Washington, DC: U.S. Department of Agriculture, Economic Research Service.

Borusyak, K., Jaravel, X., & Spiess, J. (2021). Revisiting event study designs: Robust and efficient estimation. ArXiv Preprint ArXiv:2108.12419.

Bradt, J.T., & Aldy, J.E. (2022). Private Benefits from Public Investment in Climate Adaptation and Resilience. Working paper.

Brody, S.D., & Highfield, W.E. (2013). Open space protection and flood mitigation: A national study. *Land Use Policy*, *32*, 89–95.

Bundy, L.R., Gensini, V.A., & Russo, M.S. (2022). Insured Corn Losses in the United States from Weather and Climate Perils. *Journal of Applied Meteorology and Climatology*, *61*(8), 969–988.

Burke, M., & Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture. *American Economic Journal: Economic Policy*, *8*(3), 106–140.

Callaway, B., & Sant'Anna, P.H.C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230.

Cao, J., & Lu, S. (2019). Synthetic control inference for staggered adoption: Estimating the dynamic effects of board gender diversity policies. ArXiv Preprint ArXiv:1912.06320.

Carleton, T. A., & Hsiang, S.M. (2016). Social and economic impacts of climate. *Science*, *353*(6304), aad9837–aad9837.

Carter, C., Cui, X., Ghanem, D., & Mérel, P. (2018). Identifying the economic impacts of climate change on agriculture. *Annual Review of Resource Economics*, *10*(1), 361–380.

Carter, N., Horn, D., Boyd, E., Lipiec, E., Stubbs, M., Ramseur, J., & Normand, A. (2019). Flood resilience and risk reduction: Federal assistance and programs. *Washington, DC: Congressional Research Service*.

Cattaneo, M. D., Feng, Y., Palomba, F., & Titiunik, R. (2022). Uncertainty Quantification in Synthetic Controls with Staggered Treatment Adoption. ArXiv Preprint ArXiv:2210.05026.

de Chaisemartin, C., & d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, *110*(9), 2964–2996.

Chambers, R.G. (1992). On the design of agricultural policy mechanisms. *American Journal of Agricultural Economics*, *74*(3), 646–654.

Changnon, S.A., & Hewings, G.J.D. (2001). Losses from weather extremes in the United States. *Natural Hazards Review*, *2*(3), 113–123.

Claassen, R., Duquette, E.N., & Smith, D.J. (2018). Additionality in US agricultural conservation programs. *Land Economics*, *94*(1), 19–35.

Claassen, R., Langpap, C., & Wu, J. (2017). Impacts of Federal Crop Insurance on Land Use and Environmental Quality. *American Journal of Agricultural Economics, 99*(3), 592–613. http://dx.doi.org/10.1093/ajae/aaw075

Coble, K., & Barnett, B. (2013). Why Do We Subsidize Crop Insurance? *American Journal of Agricultural Economics*, *95*(2), 498–504. Available at: https://econpapers.repec.org/RePEc:oup:ajagec:v:95:y:2013:i:2:p:498-504

Connor, L., Rejesus, R.M., & Yasar, M. (2021). Crop insurance participation and cover crop use: Evidence from Indiana county-level data. *Applied Economic Perspectives and Policy*.

Croke, J., Thompson, C., & Fryirs, K. (2017). Prioritising the placement of riparian vegetation to reduce flood risk and end-of-catchment sediment yields: Important considerations in hydrologically-variable regions. *Journal of Environmental Management*, *190*, 9–19.

Darby, S.E. (1999). Effect of riparian vegetation on flow resistance and flood potential. *Journal of Hydraulic Engineering*, *125*(5), 443–454.

DeLay, N. (2019). The impact of federal crop insurance on the conservation reserve program. *Agricultural and Resource Economics Review*, *48*(2), 297–327.

Delgado, J., Groffman, P., Nearing, M., Goddard, T., Reicosky, D., Lal, R., Kitchen, N.R., Rice, C.W., Towery, D., & Salon, P. (2011). Conservation practices to mitigate and adapt to climate change. *Journal of Soil and Water Conservation*, *66*(4), 118A-129A.

Di Falco, S., Adinolfi, F., Bozzola, M., & Capitanio, F. (2014). Crop insurance as a strategy for adapting to climate change. *Journal of Agricultural Economics*, *65*(2), 485–504.

Doudchenko, N., & Imbens, G.W. (2016). *Balancing, regression, difference-in-differences and synthetic control methods: A synthesis*. National Bureau of Economic Research.

English, B.C., Smith, S.A., Menard, R.J., Hughes, D.W., & Gunderson, M. (2021). Estimated Economic Impacts of the 2019 Midwest Floods. *Economics of Disasters and Climate Change*, *5*(3), 431–448.

Farrin, K., Miranda, M.J., & O'Donoghue, E. (2016). *How do time and money affect agricultural insurance uptake? A new approach to farm risk management analysis.* Economic Research Report ERR-212, U.S. Department of Agriculture, Economic Research Service, Washington, DC, 2016.

Feng, H., Hennessy, D.A., & Miao, R. (2013). The effects of government payments on cropland acreage, conservation reserve program enrollment, and grassland conversion in the Dakotas. *American Journal of Agricultural Economics*, *95*(2), 412–418.

Ferman, B., & Pinto, C. (2021). Synthetic controls with imperfect pretreatment fit. *Quantitative Economics*, *12*(4), 1197–1221.

Ferraro, P.J. (2008). Asymmetric information and contract design for payments for environmental services. *Ecological Economics*, *65*(4), 810–821.

Ferraro, P.J., & Simpson, R.D. (2002). The cost-effectiveness of conservation payments. *Land Economics*, *78*(3), 339–353.

Fischer, C., & Preonas, L. (2010). Combining Policies for Renewable Energy: Is the Whole Less Than the Sum of Its Parts? *International Review of Environmental and Resource Economics*, *4*(1), 51–92. https://doi.org/10.1561/101.00000030

Fleckenstein, M., Lythgoe, A., Lu, J., Thompson, N., Doering, O., Harden, S., Getson, J.M., & Prokopy, L. (2020). Crop insurance: A barrier to conservation adoption? *Journal of Environmental Management*, *276*, 111223.

Fleming, P. (2017). Agricultural cost sharing and water quality in the Chesapeake Bay: Estimating indirect effects of environmental payments. *American Journal of Agricultural Economics*, *99*(5), 1208–1227.

Fleming, P., Lichtenberg, E., & Newburn, D.A. (2018). Evaluating impacts of agricultural cost sharing on water quality: Additionality, crowding In, and slippage. *Journal of Environmental Economics and Management*, *92*, 1–19.

Fleming, P., Lichtenberg, E., & Newburn, D.A. (2020). Water quality trading in the presence of conservation subsidies. *Land Economics*, *96*(4), 552–572.

Galloway, G.E. (1995). Learning from the Mississippi flood of 1993: Impacts, management issues, and areas for research. *US-Italy Research Workshop on the Hydrometeorology, Impacts, and Management of Extreme Floods*.

Glauber, J.W. (2004). Crop Insurance Reconsidered. *American Journal of Agricultural Economics*, *86*(5), 1179–1195.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*(2), 254–277.

Ifft, J., Rajagopal, D., & Weldzuis, R. (2019). Ethanol plant location and land use: A case study of CRP and the ethanol mandate. *Applied Economic Perspectives and Policy*, *41*(1), 37–55.

Jack, B.K., Kousky, C., & Sims, K.R.E. (2008). Designing payments for ecosystem services: Lessons from previous experience with incentive-based mechanisms. *Proceedings of the National Academy of Sciences*, *105*(28), 9465–9470.

Karwowski, N. (2022). *Estimating the Effect of Easements on Agricultural Production*. National Bureau of Economic Research.

Kousky, C., Olmstead, S.M., Walls, M.A., & Macauley, M. (2013). Strategically placing green infrastructure: cost-effective land conservation in the floodplain. *Environmental Science & Technology*, *47*(8), 3563–3570.

Kousky, C., & Walls, M. (2014). Floodplain conservation as a flood mitigation strategy: Examining costs and benefits. *Ecological Economics*, *104*, 119–128.

Kreif, N., Grieve, R., Hangartner, D., Turner, A.J., Nikolova, S., & Sutton, M. (2016). Examination of the synthetic control method for evaluating health policies with multiple treated units. *Health Economics*, *25*(12), 1514–1528.

Lichtenberg, E. (2004). Cost-responsiveness of conservation practice adoption: A revealed preference approach. *Journal of Agricultural and Resource Economics*, 420–435.

Lichtenberg, E. (2007). Tenants, landlords, and soil conservation. *American Journal of Agricultural Economics*, *89*(2), 294–307.

Lichtenberg, E. (2021). Additionality in payment for ecosystem services programs: Agricultural conservation subsidies in Maryland. *Land Economics*, *97*(2), 305–320.

Lichtenberg, E., & Smith-Ramirez, R. (2011). Slippage in conservation cost sharing. *American Journal of Agricultural Economics*, *93*(1), 113–129.

Lobell, D.B., Roberts, M. J., Schlenker, W., Braun, N., Little, B.B., Rejesus, R.M., & Hammer, G.L. (2014). Greater sensitivity to drought accompanies maize yield increase in the US Midwest. *Science*, *344*(6183), 516–519.

Lynch, L., & Brown, C. (2000). Landowner decision making about riparian buffers. *Journal of Agricultural and Applied Economics*, *32*(1379-2016–113193), 585–596.

Mason-McLean, L. (2020). *Riparian buffer strips and their effectiveness as a natural flood management measure*. (Doctoral dissertation, Heriot-Watt University).

Mcleman, R., & Smit, B. (2006). Vulnerability to climate change hazards and risks: crop and flood insurance. *Canadian Geographer/Le Géographe Canadien*, *50*(2), 217–226.

Mezzatesta, M., Newburn, D.A., & Woodward, R.T. (2013). Additionality and the adoption of farm conservation practices. *Land Economics*, *89*(4), 722–742.

Miao, R., Feng, H., Hennessy, D.A., & Du, X. (2016). Assessing cost-effectiveness of the Conservation Reserve Program (CRP) and interactions between the CRP and crop insurance. *Land Economics*, *92*(4), 593–617.

Michler, J. D., Baylis, K., Arends-Kuenning, M., & Mazvimavi, K. (2019). Conservation agriculture and climate resilience. *Journal of Environmental Economics and Management*, *93*, 148–169.

Moore, M.R., & Huang, H.H. (2019). 3. Farming under Weather Risk: Adaptation, Moral Hazard, and Selection on Moral Hazard. In *Agricultural Productivity and Producer Behavior* (pp. 77–124). University of Chicago Press.

Ortiz-Bobea, A. (2021). The empirical analysis of climate change impacts and adaptation in agriculture. In *Handbook of agricultural economics* (Vol. 5, pp. 3981–4073). Elsevier.

Ortiz-Bobea, A., Ault, T. R., Carrillo, C. M., Chambers, R. G., & Lobell, D. B. (2021). Anthropogenic climate change has slowed global agricultural productivity growth. *Nature Climate Change*, *11*(4), 306–312.

Ortiz-Bobea, A., Knippenberg, E., & Chambers, R. G. (2018). Growing climatic sensitivity of US agriculture linked to technological change and regional specialization. *Science Advances*, *4*(12), eaat4343.

Prokopy, L. S., Floress, K., Arbuckle, J. G., Church, S.P., Eanes, F.R., Gao, Y., Gramig, B.M., Ranjan, P., & Singh, A.S. (2019). Adoption of agricultural conservation practices in the

United States: Evidence from 35 years of quantitative literature. *Journal of Soil and Water Conservation*, *74*(5), 520–534.

Reyes, J., & Elias, E. (2019). Spatio-temporal variation of crop loss in the United States from 2001 to 2016. *Environmental Research Letters*, *14*(7), 74017.

Reyes, J., Elias, E., Haacker, E., Kremen, A., Parker, L., & Rottler, C. (2020). Assessing agricultural risk management using historic crop insurance loss data over the ogallala aquifer. *Agricultural Water Management*, *232*, 106000.

Ribaudo, M., & Shortle, J. (2019). Reflections on 40 years of applied economics research on agriculture and water quality. *Agricultural and Resource Economics Review*, *48*(3), 519–530.

Robbins, M.W., Saunders, J., & Kilmer, B. (2017). A framework for synthetic control methods with high-dimensional, micro-level data: evaluating a neighborhood-specific crime intervention. *Journal of the American Statistical Association*, *112*(517), 109–126.

Rosch, S. (2021). Federal Crop Insurance: A Primer. *Congressional Research Service*, *R46686*. https://crsreports.congress.gov

Rosenzweig, C., Tubiello, F.N., Goldberg, R., Mills, E., & Bloomfield, J. (2002). Increased crop damage in the US from excess precipitation under climate change. *Global Environmental Change*, *12*(3), 197–202.

Roth, J., Sant'Anna, P. H. C., Bilinski, A., & Poe, J. (2023). What's trending in difference-in-differences? A synthesis of the recent econometrics literature. Journal of Econometrics.

Rubin, D.B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology*, *66*(5), 688.

Schlenker, W., & Roberts, M.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. http://www.pnas.org/content/106/37/15594.abstract

Schoengold, K., Ding, Y., & Headlee, R. (2015). The impact of AD HOC disaster and crop insurance programs on the use of risk-reducing conservation tillage practices. *American Journal of Agricultural Economics*, *97*(3), 897–919.

Shirzaei, M., Khoshmanesh, M., Ojha, C., Werth, S., Kerner, H., Carlson, G., Sherpa, S. F., Zhai, G., & Lee, J.-C. (2021). Persistent impact of spring floods on crop loss in US Midwest. *Weather and Climate Extremes*, *34*, 100392.

Spalding, M.D., Ruffo, S., Lacambra, C., Meliane, I., Hale, L.Z., Shepard, C.C., & Beck, M.W. (2014). The role of ecosystems in coastal protection: Adapting to climate change and coastal hazards. *Ocean & Coastal Management*, *90*, 50–57.

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, *225*(2), 175–199.

Tack, J., Coble, K., & Barnett, B. (2018). Warming temperatures will likely induce higher premium rates and government outlays for the US crop insurance program. *Agricultural Economics*, *49*(5), 635–647.

Taylor, C.A., & Druckenmiller, H. (2022). Wetlands, Flooding, and the Clean Water Act. *American Economic Review*, *112*(4), 1334–1363.

Wang, H. (2021). Flood Your Neighbors: Spillover Effects of Levee Building. Working Paper.

Wing, O.E.J., Lehman, W., Bates, P.D., Sampson, C.C., Quinn, N., Smith, A.M., Neal, J.C., Porter, J.R., & Kousky, C. (2022). Inequitable patterns of US flood risk in the Anthropocene. *Nature Climate Change*, *12*(2), 156–162.

Woodard, J.D., Schnitkey, G.D., Sherrick, B.J., Lozano-Gracia, N., & Anselin, L. (2012). A spatial econometric analysis of loss experience in the US crop insurance program. *Journal of Risk and Insurance*, *79*(1), 261–286.

Woodard, J.D., Sherrick, B.J., & Schnitkey, G.D. (2011). Actuarial impacts of loss cost ratio ratemaking in US crop insurance programs. *Journal of Agricultural and Resource Economics*, 211–228.

Woodard, J.D., & Verteramo-Chiu, L.J. (2017). Efficiency impacts of utilizing soil data in the pricing of the federal crop insurance program. *American Journal of Agricultural Economics*, *99*(3), 757–772.

Wu, J. (1999). Crop Insurance, Acreage Decisions, and Nonpoint-Source Pollution. *American Journal of Agricultural Economics*, *81*(2), 305–320. http://dx.doi.org/10.2307/1244583

Wu, J., & Babcock, B.A. (1996). Contract design for the purchase of environmental goods from agriculture. *American Journal of Agricultural Economics*, *78*(4), 935–945.

Wunder, S., Börner, J., Ezzine-de-Blas, D., Feder, S., & Pagiola, S. (2020). Payments for environmental services: Past performance and pending potentials. *Annual Review of Resource Economics*, *12*, 209–234.

Yu, J., Goodrich, B., & Graven, A. (2022). Competing farm programs: Does the introduction of a risk management program reduce the enrollment in the Conservation Reserve Program? *Journal of the Agricultural and Applied Economics Association*, *1*(3), 320–333.

Tables and Figures

Table 1. Timing Variation of Conservation Reserve Enhancement Program (CREP) Availability and Participation

	Number of Sample County				Fiscal Year of Program Availability/Participation	
State	Total	Availability	Participation	N/A	Availability (min, max)	Participation (min, max)
AR	18	4	3	14	2002, 2007	2002, 2008
IL	54	39	37	15	1998, 2011	1998, 2012
IN	51	40	38	11	2006, 2011	2006, 2022
IA	84	35	30	49	2002, 2002	2003, 2021
KY	8	2	2	6	2007, 2007	2007, 2008
LA	14	10	6	4	2006, 2011	2006, 2006
MN	40	40	40	0	1999, 2006	1999, 2008
MO	32	22	17	10	2001, 2007	2002, 2008
NE	18	13	13	5	2003, 2003	2003, 2004
OH	36	29	28	7	2000, 2005	2000, 2006
SD	18	9	9	9	2010, 2010	2010, 2011
MS	0	0	0	8	N/A	N/A
TN	0	0	0	3	N/A	N/A
Total	384	243	223	141		

Note: The table presents the number of counties with available CREP funding and the number of counties with non-zero acres of program enrollment (participation) by state. The table also presents the first and last fiscal years of program availability and participation by state.

Source: USDA Farm Service Agency

Table 2. Descriptive Statistics: Main Analysis

Variables		Mean	SD	Min	Max
Crop Loss Experience (county-by-year)					
Indemnity payouts per flooded crop acre ($/acre, nominal)	Treated	53	88	0	733
	Untreated	67	101	0	872
Indemnity payout ($1,000s, nominal)	Treated	52	260	0	7,175
	Untreated	127	835	0	31,974
Crop acres loss due to flooding (acre)	Treated	354	1,186	0	21,031
	Untreated	652	2,542	0	67,382
Federal Crop Insurance Program Participation (county-by-year)					
Acres insured (1,000s)	Treated	166	100	4	585
	Untreated	142	93	2	531
Coverage level insured (%, area-weighted)	Treated	71	8	47	86
	Untreated	69	8	42	85
Conservation Reserve Enhance Program (CREP) (county avg. and county-by-year)					
= 1 if CREP is available by 2011, county-level avg.	Treated	1	0	1	1
= 1 if CREP has nonzero acres enrolled by 2022, county-level avg.	Treated	0.92	0.28	0	1
Number of acres enrolled	Treated	727	1,857	0	20,197
Annual program payments ($1,000s, nominal)	Treated	117	323	0	4,819
Weather (county-by-year)					
Total Precipitation (mm)					
Post-harvest, Oct.-Mar. 1988-1997	Treated	356	159	146	871
	Untreated	438	230	146	896
Growing season, Apr.-Sept. 1989-1997	Treated	632	75	433	931
	Untreated	660	81	482	944
Growing degree days (10-29 Celsius)					
Post-harvest, Oct.-Mar. 1988-1997	Treated	194	163	53	1,068
	Untreated	270	200	71	1,055
Growing season, Apr.-Sept. 1989-1997	Treated	1,629	271	1,206	2,692
	Untreated	1,790	327	1,261	2,644
Num. Obs. (county-by-year): Treated 8,262 (243-by-34); Untreated 4,794 (141-by-34)					

Note: The table presents summary statistics of variables used in the main analysis for 384 sample counties during 1989-2022. Treated group refers to counties that introduced CREP by 2011 and untreated group refers to counties that never introduced CREP by 2011.

Source: USDA Risk Management Agency and Farm Service Agency, and Schlenker and Roberts (2009)

Table 3. Descriptive Statistics: Program Effect Heterogeneity Analysis

Variables	Mean	SD	Min	Max
Estimated Program Effect $\hat{\tau}_{jk}$ $(0 \leq k \leq 10)$				
ATT: Indemnity payouts per flooded crop acre ($/acre, nominal)	-23.1	93.3	-440.8	615.5
Conservation Reserve Enhance Program (CREP)				
Duration of CREP availability in years	4.9	3.1	0	10
Number of acres enrolled	1,174.1	2,358.3	0.0	20,197.2
Inter-County Spillover Effects				
Number of surrounding counties with CREP	4.9	1.5	1.0	9.0
Alternative flood mitigation measure				
Leveed area (acre)	3.9	17.1	0.0	140.6
Farm Resource Region				
= 1 if a county is located in the Mississippi River Portal region (downstream)	0.1	0.2	0.0	1.0
Federal Crop Insurance Program Participation				
Coverage level insured (%, area-weighted)	73.0	6.2	50.5	86.5
Acres insured (1,000s)	184,799.1	91,414.5	12,691	559,230
Community Resilience to Natural Hazard				
FEMA Community Risk Factor	1.1	0.1	0.8	1.6
Weather during growing season, Apr.-Sept.				
Total precipitation (mm)	623.5	153.4	235.1	1,519.4
Total growing degree days (10-29 Celsius)	1,723.6	294.8	1,031.7	2,848.7
Num. Obs. (treated county-by-post policy event time): 2,592 (243-by-11 less 81)				

Note: The table presents summary statistics of variables used in the analysis of program effect heterogeneity for 243 counties that introduced CREP by 2011. Out of 2673 estimated county-by-event time post-policy effects, 81 estimates in 2020 and 2021 are dropped due to unavailability of weather data.

Source: USDA Risk Management Agency and Farm Service Agency, the U.S. Army Corps of Engineers National Levee Database, the Federal Emergency Management Agency (FEMA), and Schlenker and Roberts (2009)

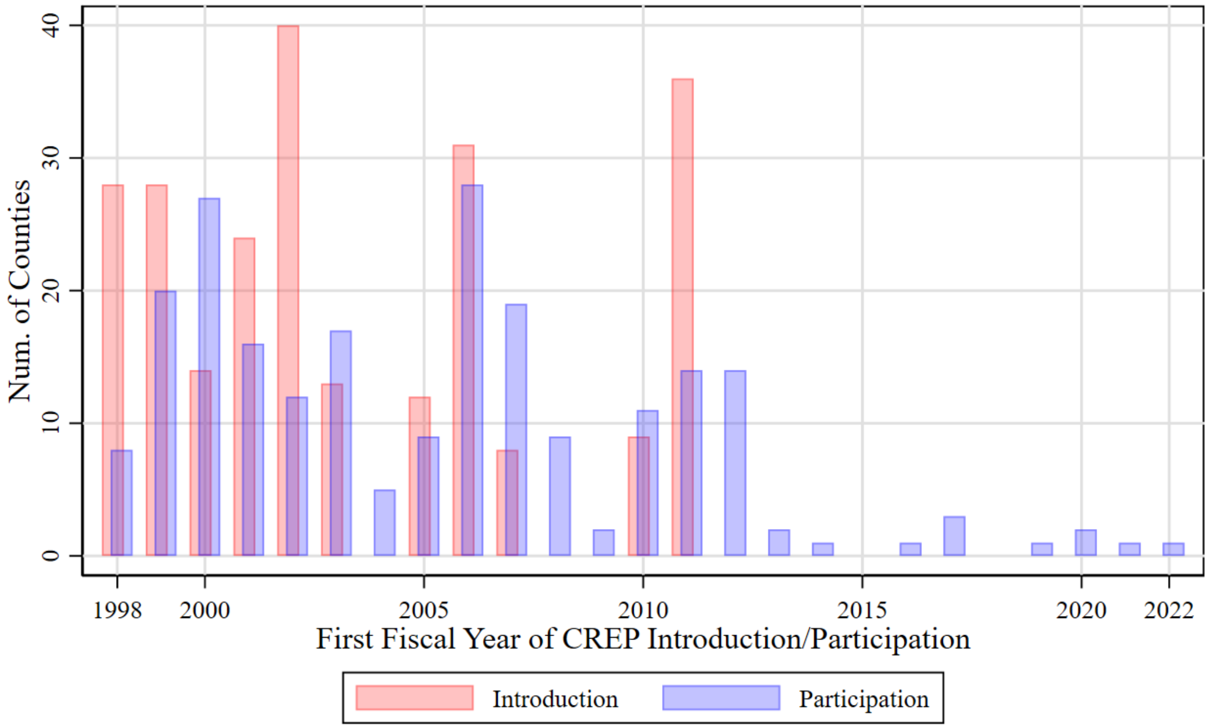
Table 4. Descriptive Analysis: Program Effect Heterogeneity

Outcome: ATT Indemnity payouts per flooded crop acre ($/acre, nominal)	Estimate
A. Conservation Reserve Enhance Program (CREP)	
Duration of CREP availability in years	-2***
	(.6)
Number of acres enrolled, standardized	-10.1***
	(2.1)
B. Inter-County Spillover Effects	
Number of surrounding counties with CREP, standardized	.5
	(1.9)
C. Alternative flood mitigation measure	
Leveed Area (acre), standardized	11.4***
	(2.8)
D. Farm Resource Region	
= 1 if a county is located in the Mississippi River Portal (downstream)	-88.7***
	(15.3)
E. Federal Crop Insurance Program Participation (county-by-year)	
Coverage level insured (%, area-weighted), standardized	-10.1***
	(2.3)
Acres insured (1,000s), standardized	7.7***
	(2)
F. Community Resilience to Natural Hazard	
FEMA Community Risk Factor	-4.2
	(16.7)
G. Weather during growing season, Apr.-Sept. (county-by-year)	
Total precipitation (mm) Apr-Sept, standardized	10***
	(1.9)
Total Growing degree days (10-29 Celsius), standardized	14.3***
	(2.8)
Constant	-4.4
	(17.9)
Observations (county-by-event time)	2,592
R-squared	.05
F-stat	14.3
Outcome Mean	-23.1

Note: The table presents a linear association between the estimated loss mitigation benefits of CREP and county-level characteristics, obtained from a multivariate regression. Standard errors are in parentheses and clustered at the county-level.

*** $p<.01$, ** $p<.05$, * $p<.1$

Figure 1. Timing Variation of CREP Introduction and Participation, 1998-2022

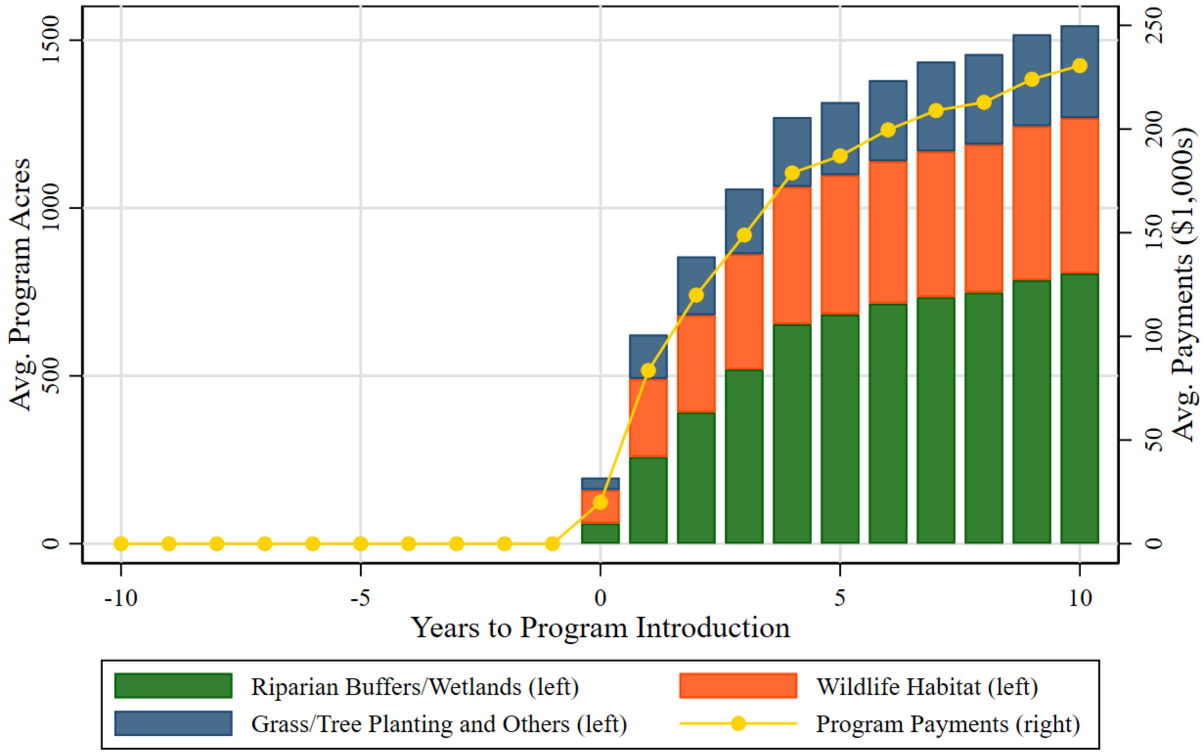


Total: 384 counties from 13 states with 11 different timings of CREP introduction
CREP Available: 243 counties from 11 states
CREP Participation: 223 counties from 11 states
CREP N/A: 141 counties from 12 states
Source: USDA-Farm Service Agency

Note: The graph shows the count of counties that introduced Conservation Reserve Enhancement Program (CREP) in any year before 2012 (y-axis) by the initial year of CREP introduction or participation (x-axis).

Source: USDA Farm Service Agency

Figure 2. Program Enrolled Acres and Payments in CREP by Event Time

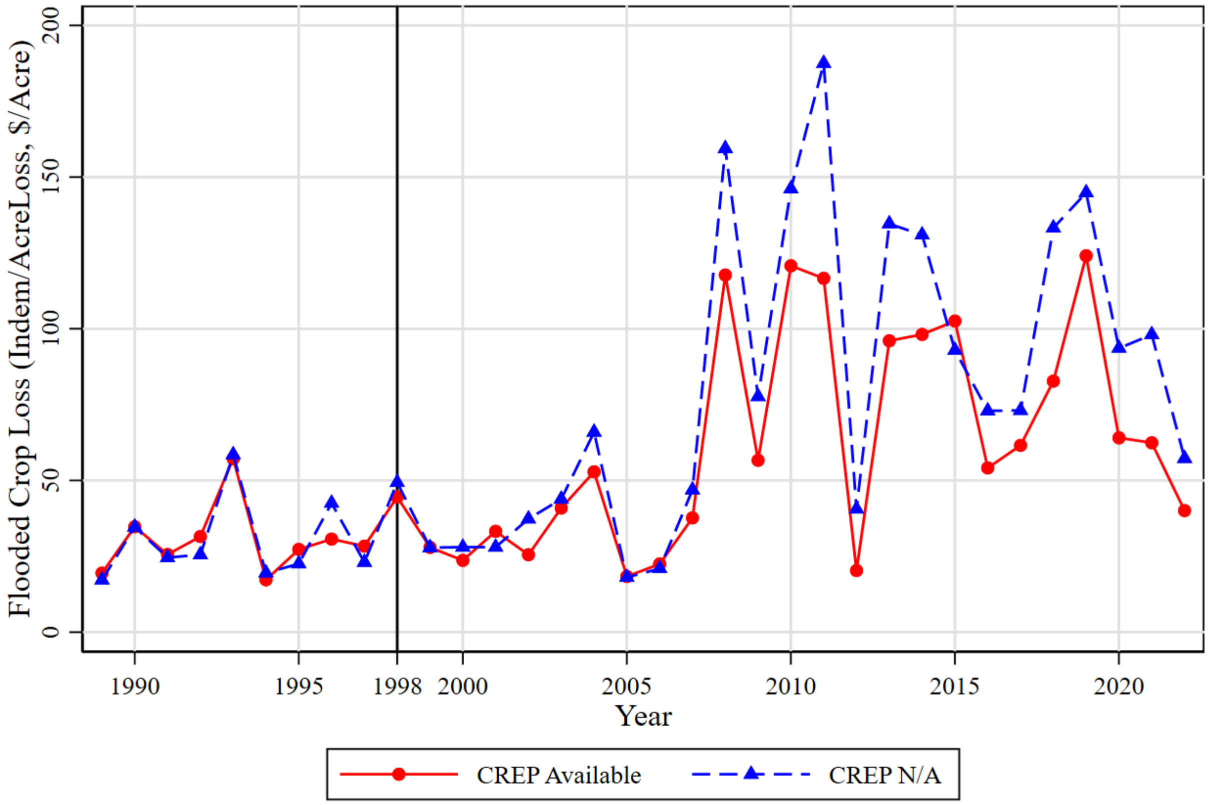


Unit of Obs.: County-by-Year (CREP Available 243, CREP Participation 223, CREP N/A 141)
Program Acre: Mean = 1151, SD = 2332, Min = 0, Max = 20197, N = 2673
Program Payment ($1,000s): Mean = 165, SD = 374, Min = 0, Max = 4379, N = 2673
Source: USDA-Farm Service Agency

Note: The graph shows the average number of acres enrolled in the Conservation Reserve Enhancement Program (CREP) at the county level (y-axis left), as well as the corresponding payments made (y-axis right, in nominal terms), for 243 counties with CREP availability. The x-axis represents the length of exposure to the program availability (event time).

Source: USDA Farm Service Agency

Figure 3. Trend in Flooded Crop Loss in the Federal Crop Insurance Program, 1998-2022

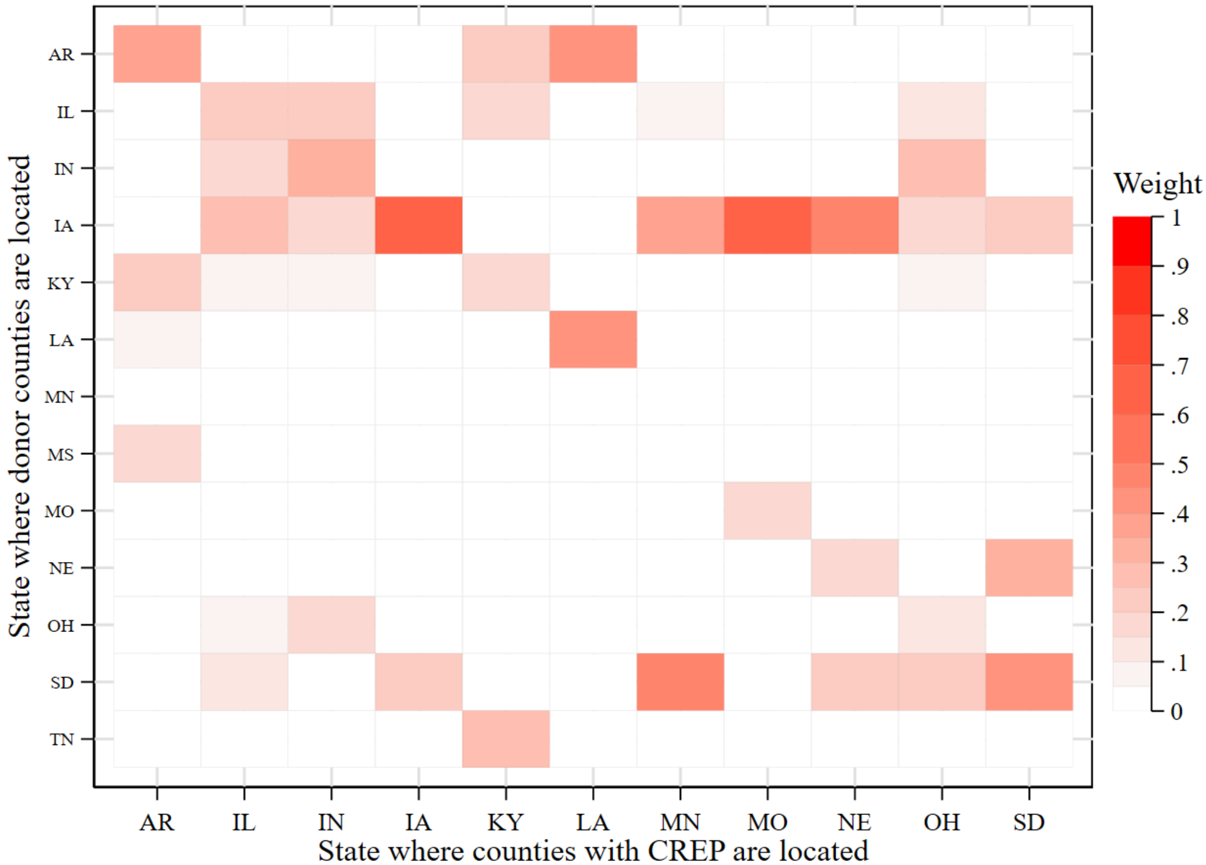


CREP Available: 243 counties from 11 states; Mean = 53, SD = 88, Min = 0, Max = 733, N = 8262
CREP N/A: 141 counties from 12 states; Mean = 67, SD = 101, Min = 0, Max = 872, N = 4794

Note: The graph shows trends in the average indemnity payouts (in nominal terms) per flooded crop acre at the county level (y-axis), comparing counties with and without Conservation Reserve Enhancement Program (CREP) over the sample years 1989-2022 (x-axis).

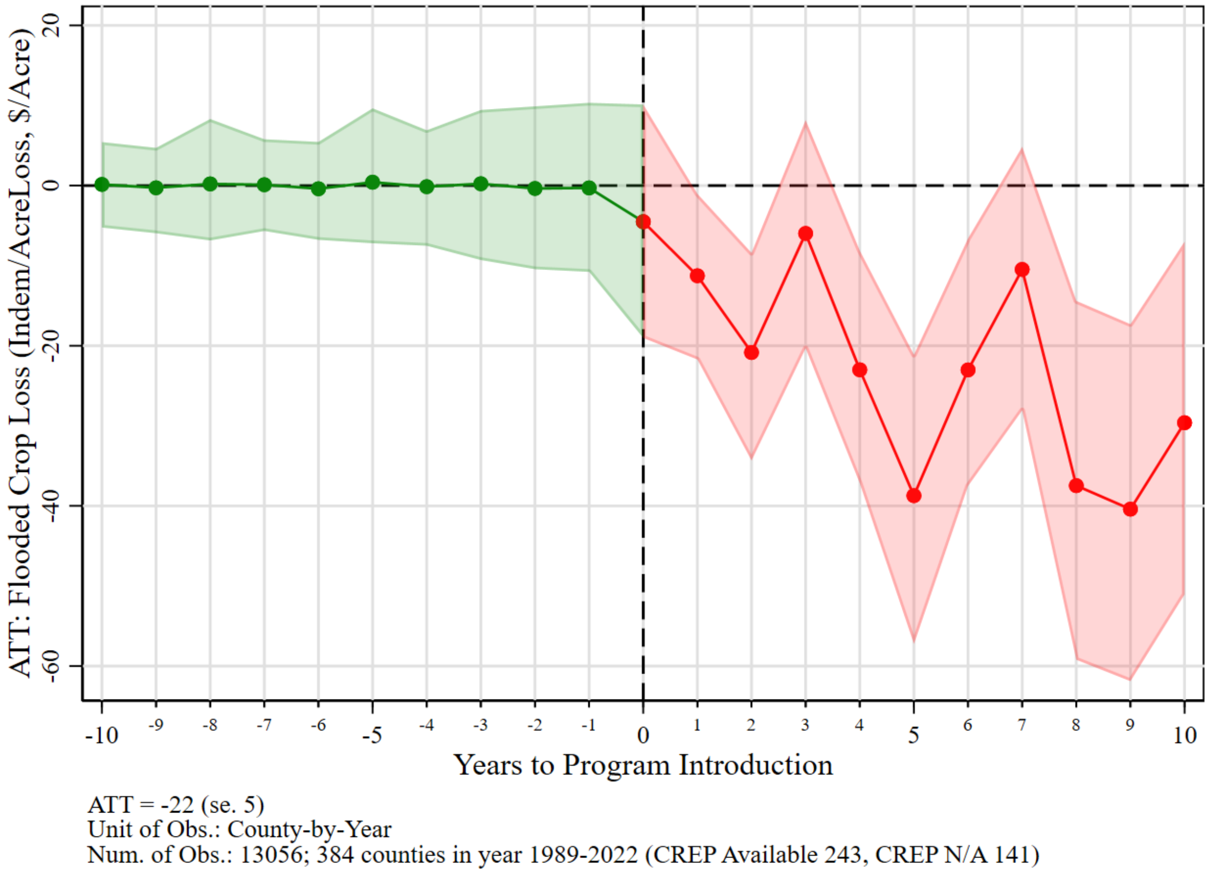
Source: USDA Risk Management Agency and Farm Service Agency

Figure 4. Spatial Distribution of Synthetic Control Weight for Donor Units



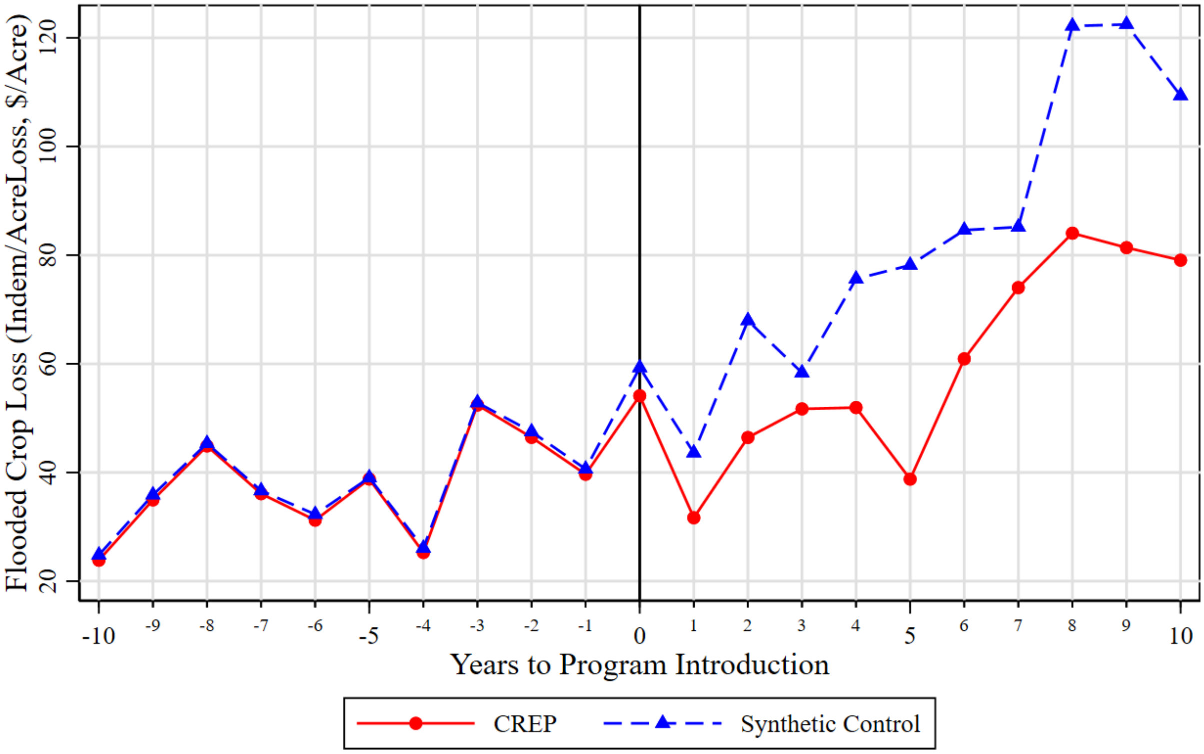
Note: The figure presents the distribution of weights assigned to donor counties in each state when constructing synthetic controls for treated counties in a given state. When multiple counties in state a are treated, the sum of synthetic control weights for all treated counties in state a equals the number of treated counties in a given state, N_a^{trt}. For all treated counties in state a, total synthetic control weights of donor counties in each state b equals $\sum_{j\in a, i\in b} w_{ji} = W_{ab}$. Then, the average share of synthetic control weight assigned to all donor counties in state b for all treated counties in state a is $\frac{W_{ab}}{N_a^{trt}}$, where the sum over all potential donor states equals 1, $\sum_b \frac{W_{ab}}{N_a^{trt}} = 1$. The graph presents $\frac{W_{ab}}{N_a^{trt}}$ for each combination of state a where treated counties are located and state b where donor counties are located.

Figure 5. Estimated Impact of CREP Introduction on Flooded Crop Damage



Note: The graph shows the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss (indemnity payouts per flooded crop acre in nominal terms, y-axis) across event time (x-axis) with 95 percent confidence intervals. The estimated average program effect is calculated by comparing the average change in crop loss relative to pre-policy average between counties with CREP and their synthetic controls. In addition to lagged outcomes, precipitation (mm) and growing degree days during the post-harvest (October to March) and crop growing seasons (April to September) are used as auxiliary covariates in choosing weights of donor units to construct synthetic controls.

Figure 6. Trend in Flooded Crop Loss: Counties with CREP and Synthetic Control



Pre-outcome Avg.: CREP 34, Synthetic Control 35, Pre-Diff. = -1
Post-outcome Avg.: CREP 59, Synthetic Control 82, Post-Diff = -23
Unit of Obs.: County-by-Year
Num. of Obs.: 13056; 384 counties in year 1989-2022 (CREP Available 243, CREP N/A 141)

Note: The graph shows trends in average flooded crop loss (indemnity payouts per flooded acre in nominal terms) (y-axis) in counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls by event time (x-axis).

APPENDIX A. Supplementary Materials for Synthetic Control Method

Partially pooled synthetic control method with an intercept shift estimates the counterfactual trajectory of average crop loss in the treated group by allocating weights across untreated counties to maximize the similarity between the synthetic control counties and the treated counties in terms of both *individual* and *average* pre-policy trends in crop loss (Ben-Michael et al., 2022; Doudchenko & Imbens, 2016; Ferman & Pinto, 2021). To achieve this objective, partially pooled SCM considers two imbalance measures, motivated by different interpretations of the average treatment effect on the treated (ATT_k) in equation (3): (i) the average difference in pre-policy outcome between the treated and synthetic control counties (individual fit), and (ii) the difference in average pre-policy outcome between the treated and synthetic control counties (pooled fit).

To be specific, let $\gamma_{ij} \geq 0$ denote the weight on potential donor county i to construct the synthetic control for treated county j where $\sum_i \gamma_{ij} = 1$. For each treated county $j \leq J$, let γ_j be a 1-by-N vector of the weights on potential donor counties and $\Gamma = [\gamma_1, \dots, \gamma_J] \in \Delta^{scm}$ be an N-by-J weight matrix where $\Delta^{scm} = \Delta_1^{scm} \times \dots \times \Delta_J^{scm}$. The donor pool consists of both counties where PES program was never available during the sample periods and counties where the CREP was not available until $T_j + K$ (i.e., $T_i > T_j + K$). The individual fit is measured by the root mean square of the pre-policy fits across treated counties $q^{sep}(\Gamma)$:$A.1$

$$q^{sep}(\Gamma) \equiv \sqrt{\frac{1}{J}\sum_{j=1}^{J}\frac{1}{L_j}\sum_{l=1}^{L_j}\Bigg[\underbrace{\dot{Y}_{jT_j-l} - \sum_{i=1}^{N}\gamma_{ij}\dot{Y}_{iT_j-l}}_{individual\ pre-trend\ fit}\Bigg]^2} \qquad (A.1)$$

Likewise, the pooled fit is measured by the root mean square of the pre-policy fit for the average of treated counties $q^{pool}(\Gamma)$:

$$q^{pool}(\Gamma) \equiv \sqrt{\frac{1}{L}\sum_{l=1}^{L}\Bigg[\underbrace{\frac{1}{J}\sum_{T_j>l}\dot{Y}_{jT_j-l} - \frac{1}{J}\sum_{T_j>l}\sum_{i=1}^{N}\gamma_{ij}\dot{Y}_{iT_j-l}}_{average\ pre-trend\ fit}\Bigg]^2} \qquad (A.2)$$

If all treated units can find perfect synthetic control unit ($q^{sep}(\Gamma) = 0$), then we have perfect fit for the average outcome trend for the treated group ($q^{pool}(\Gamma) = 0$). In practice, however, not all treated units have imperfect pre-treatment fit, which leads to a gap in average pre-trend outcome between the treated and synthetic control group and undermines the validity of the estimated average program effect.

Partially pooled SCM finds a set of weights Γ that minimizes the weighted average of $q^{sep}(\Gamma)$ and $q^{pool}(\Gamma)$:

$$\min_{\Gamma\in\Delta^{scm}} \nu[q^{pool}(\Gamma)]^2 + (1-\nu)[q^{sep}(\Gamma)]^2 + \lambda\|\Gamma\|_F^2, \qquad (A.3)$$

where the relative importance of the average outcome fit (pooled fit) to individual outcome fit increases with parameter $\nu \in [0,1]$.[10] To ensure the uniqueness of weights and avoid interpolation biases, a regularization penalty term λ is added (Abadie et al., 2015; Abadie & L'Hour, 2021; Arkhangelsky et al., 2021; Doudchenko & Imbens, 2016).[11] As a baseline, I follow Ben-Michael et al (2022) and set ν to be the ratio of the pooled fit to the average unit-level fit as a baseline:

$$\nu = \frac{\sqrt{\sum_{l=1}^{L}\left[\frac{1}{J}\sum_{T_j>l}\dot{Y}_{jT_j-l} - \frac{1}{J}\sum_{T_j>l}\sum_{i=1}^{N}\hat{\gamma}_{ij}^{sep}\dot{Y}_{iT_j-l}\right]^2}}{\frac{1}{J}\sum_{j=1}^{J}\sqrt{\frac{1}{L_j}\sum_{l=1}^{L_j}\left[\dot{Y}_{jT_j-l} - \sum_{i=1}^{N}\hat{\gamma}_{ij}^{sep}\dot{Y}_{iT_j-l}\right]^2}}. \qquad (A.4)$$

Using the set of weights $\hat{\gamma}_{ij}$ obtained from the equation (A.3), the resulting estimator of counterfactual average outcome of county j treated in year T_j at event time k is:

$$\hat{Y}_{jT_j+k}(\infty) = \underbrace{\frac{1}{L_j}\sum_{l=1}^{L_j} Y_{jT_j-l} - \frac{1}{L_j}\sum_{i=1,i\neq j}^{N}\sum_{l=1}^{L_j}\hat{\gamma}_{ij}Y_{iT_j-l}}_{intercept\ shift} + \underbrace{\sum_{i=1,i\neq j}^{N}\hat{\gamma}_{ij}Y_{iT_j+k}}_{weighted\ average\ of\ untreated\ outcome}, \qquad (A.5)$$

where the intercept shift equals the average pre-policy outcome difference between treated county j and its synthetic control county. Combining equations (A.5) with (2) yields a form of weighted DID estimator $\hat{\tau}_{jk}$:

$$\hat{\tau}_{jk} = \dot{Y}_{jT_j+k}(T_j) - \hat{\dot{Y}}_{jT_j+k}(\infty) \qquad (A.6)$$

$$= \left[Y_{jT_j+k}(T_j) - \frac{1}{L_j}\sum_{l=1}^{L_j} Y_{jT_j-l}\right] - \left[\sum_{i=1,\neq j}^{N}\hat{\gamma}_{ij}\, Y_{iT_j+k} - \frac{1}{L_j}\sum_{l=1}^{L_j}\sum_{i=1,\neq j}^{N}\hat{\gamma}_{ij}\, Y_{iT_j-l}\right],$$

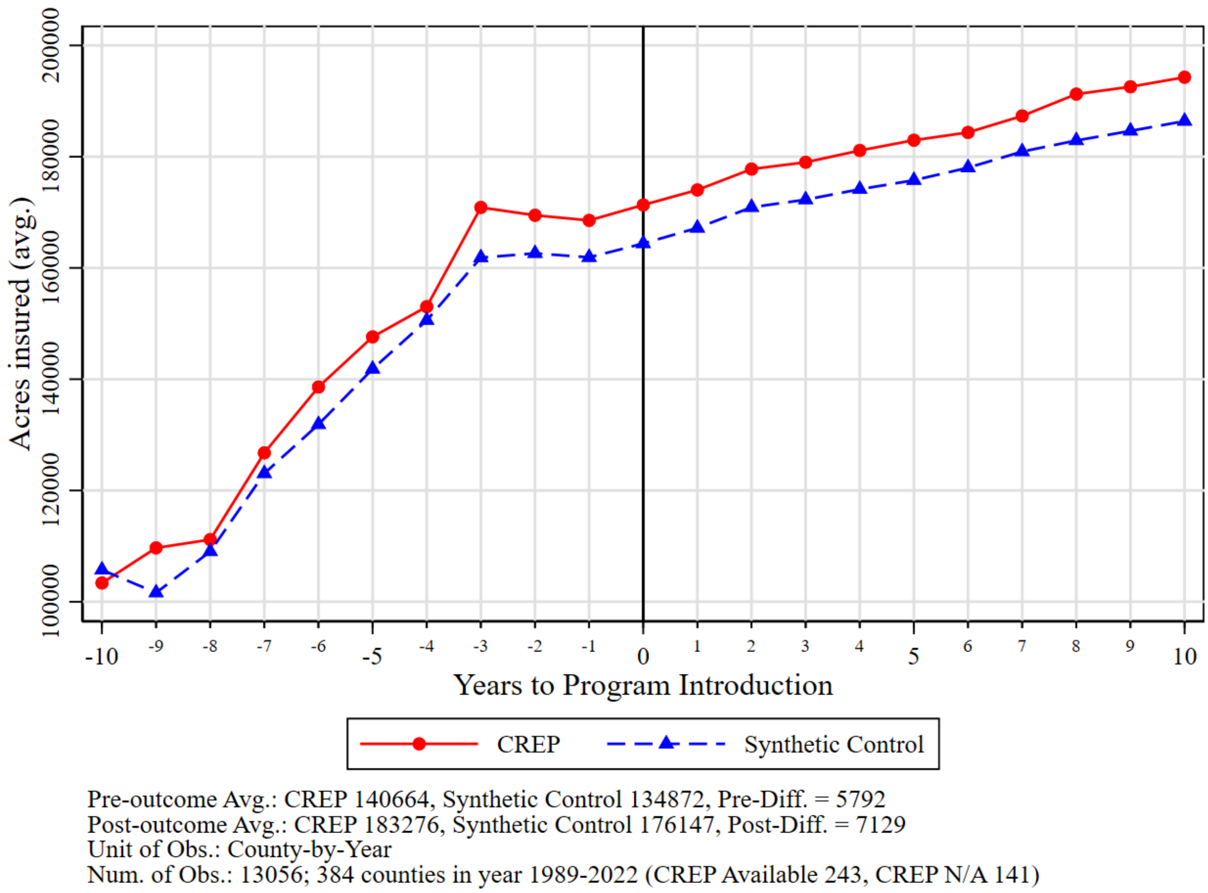
[10] In practice, both $q^{pool}(\Gamma)$ and $q^{sep}(\Gamma)$ are normalized by $q^{sep}(\hat{\Gamma}^{sep})$ where $\hat{\Gamma}^{sep}$ is a set of weights $\gamma_1, \dots, \gamma_J$ that minimizes the individual pre-policy fit only. See Ben-Michael et al (2022) for details.

[11] $\|\cdot\|_F$ is Frobenius norm defined as the square root of the sum of the absolute squares of elements in the matrix. For example, $\|\Gamma\|_F^2 = \sum_i\sum_j|\gamma_{ij}|^2$.

where weights for untreated counties $\hat{\gamma}_{ij}$ are chosen to minimize imbalance of both individual counties and average pre-policy trends in crop loss as shown in equation (A.3).

APPENDIX B. Supporting Figures for the Main Results

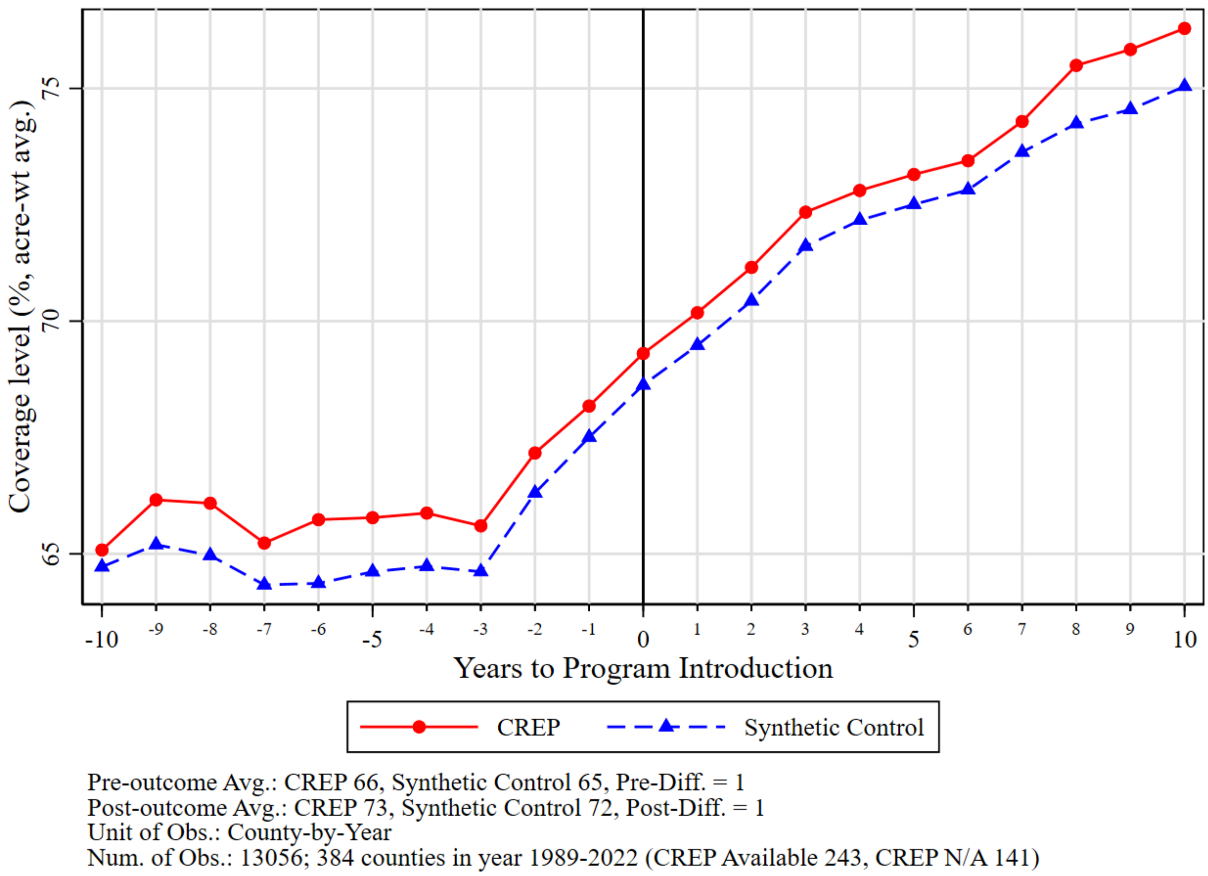
Figure B1. Trends in Acres Insured under the Federal Crop Insurance Program



Note: The graph shows trends in county-level average insured acres (y-axis) over event time (x-axis) in counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls.

Source: USDA Risk Management Agency

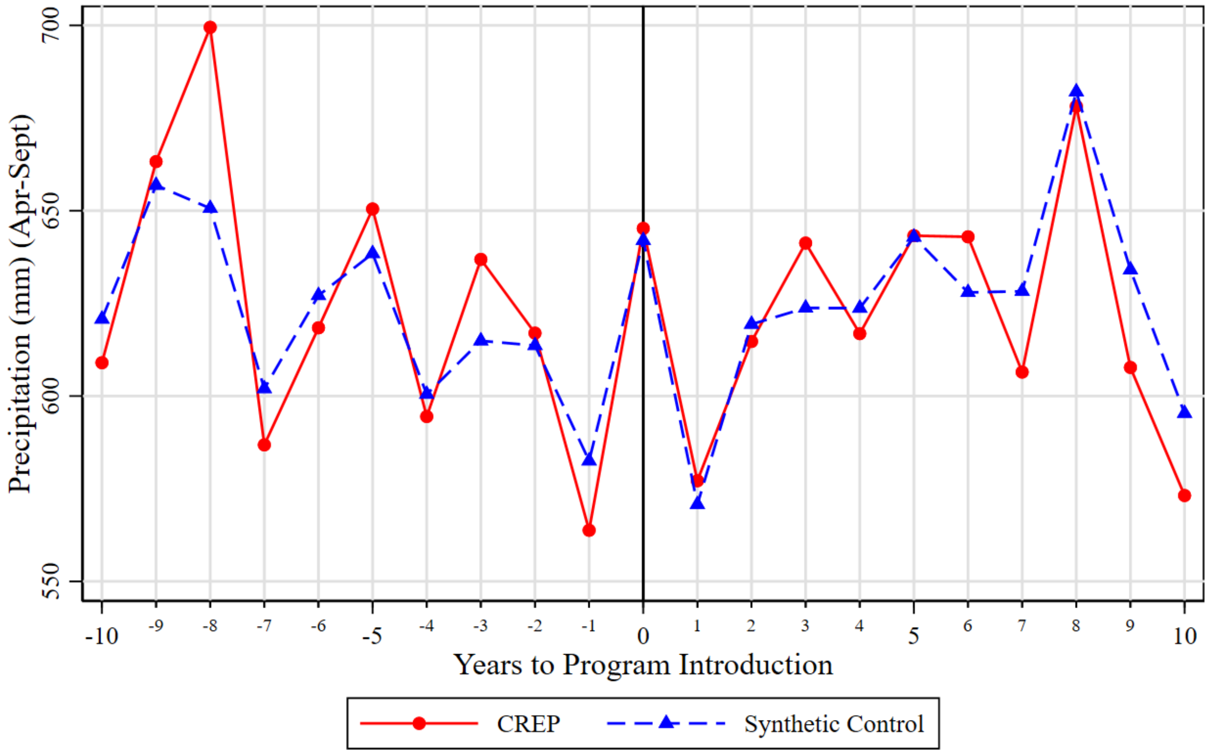
Figure B2. Trends in Insurance Coverage Level under the Federal Crop Insurance Program



Note: The graph shows how the coverage level for acres insured under the federal crop insurance program has changed over event time (x-axis) for both counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls. The y-axis represents the acreage-weighted average of the county-level coverage level.

Source: USDA Risk Management Agency

Figure B3. Trends in Precipitation during Crop Growing Season

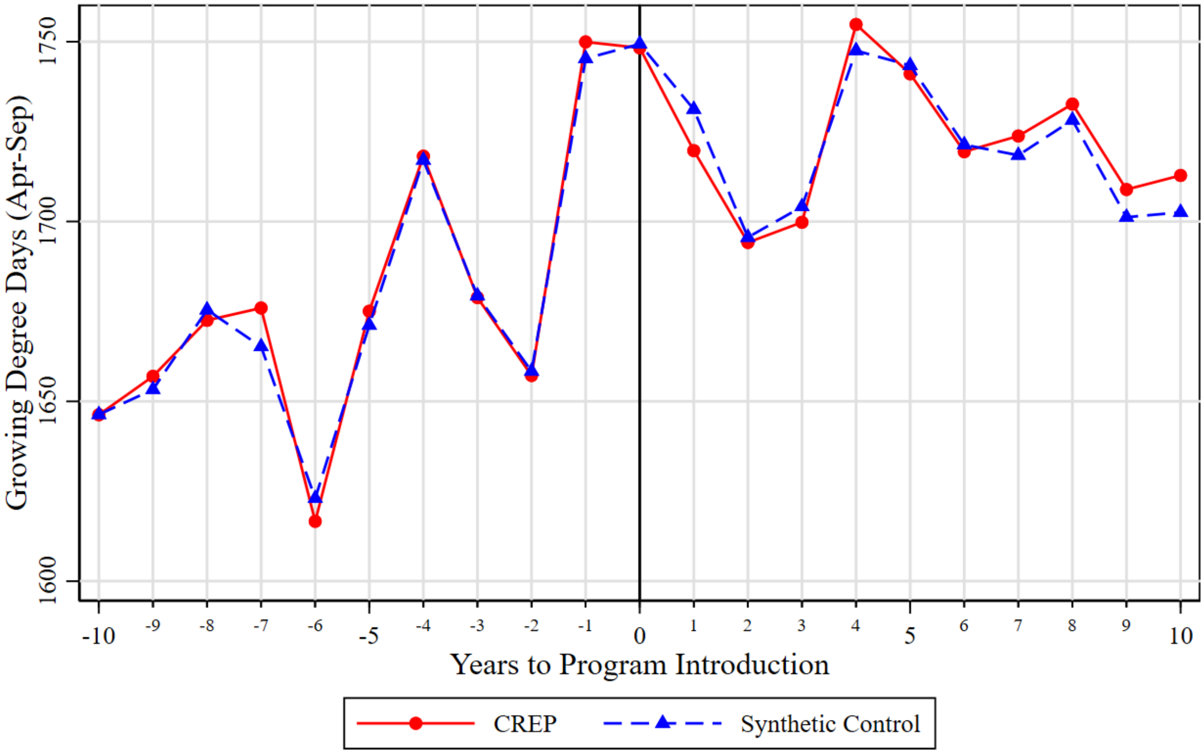


Pre-outcome Avg.: CREP 624, Synthetic Control 621, Pre-Diff. = 3
Post-outcome Avg.: CREP 624, Synthetic Control 627, Post-Diff. = -3
Unit of Obs.: County-by-Year
Num. of Obs.: 13056; 384 counties in year 1989-2022 (CREP Available 243, CREP N/A 141)

Note: The graph shows trends in county-level average total precipitation (mm) during the crop growing season (April-September) (y-axis) over event time (x-axis) for both counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls.

Source: Schlenker and Roberts (2009)

Figure B4. Trends in Growing Degree Days (10-29 Celsius) during Crop Growing Season

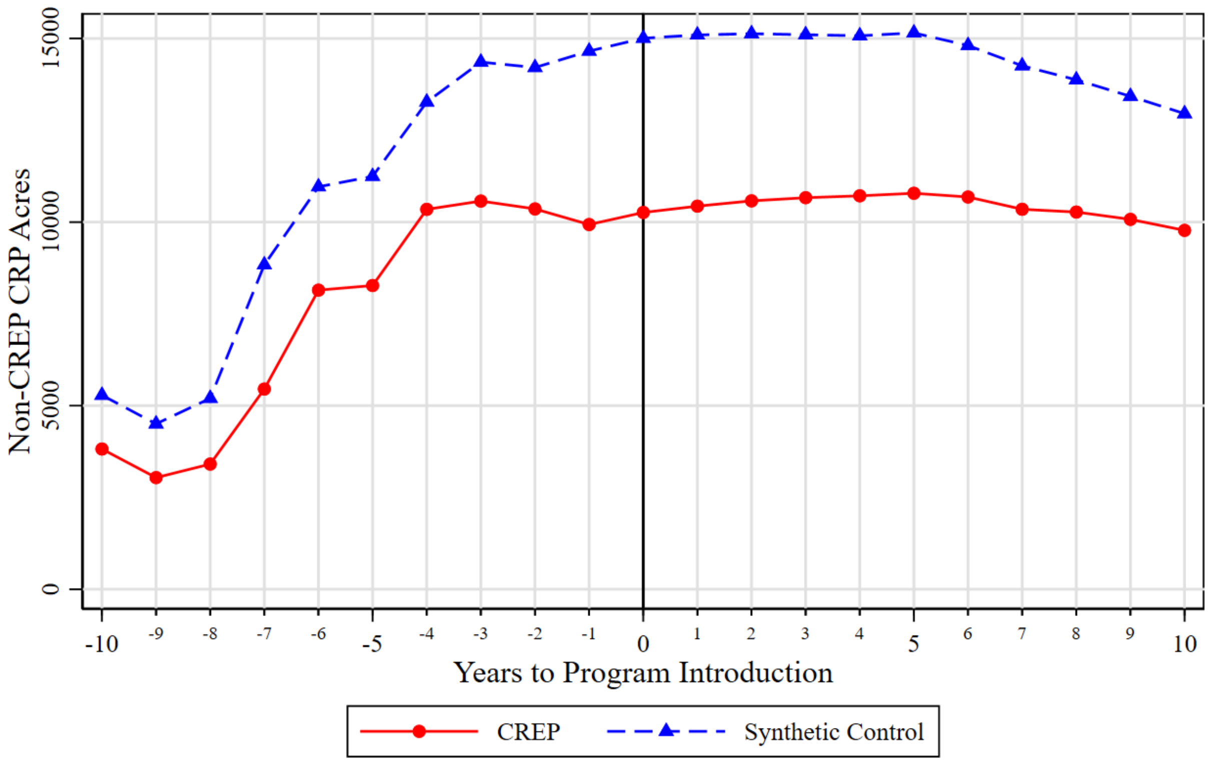


Pre-outcome Avg.: CREP 1675, Synthetic Control 1673, Pre-Diff. = 2
Post-outcome Avg.: CREP 1724, Synthetic Control 1723, Post-Diff. = 1
Unit of Obs.: County-by-Year
Num. of Obs.: 13056; 384 counties in year 1989-2022 (CREP Available 243, CREP N/A 141)

Note: The graph shows trends in county-level average growing degree days during the crop growing season (April-September) (y-axis) over event time (x-axis) for both counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls.

Source: Schlenker and Roberts (2009)

Figure B5. Trends in Conservation Reserve Program Participation (Non-CREP)

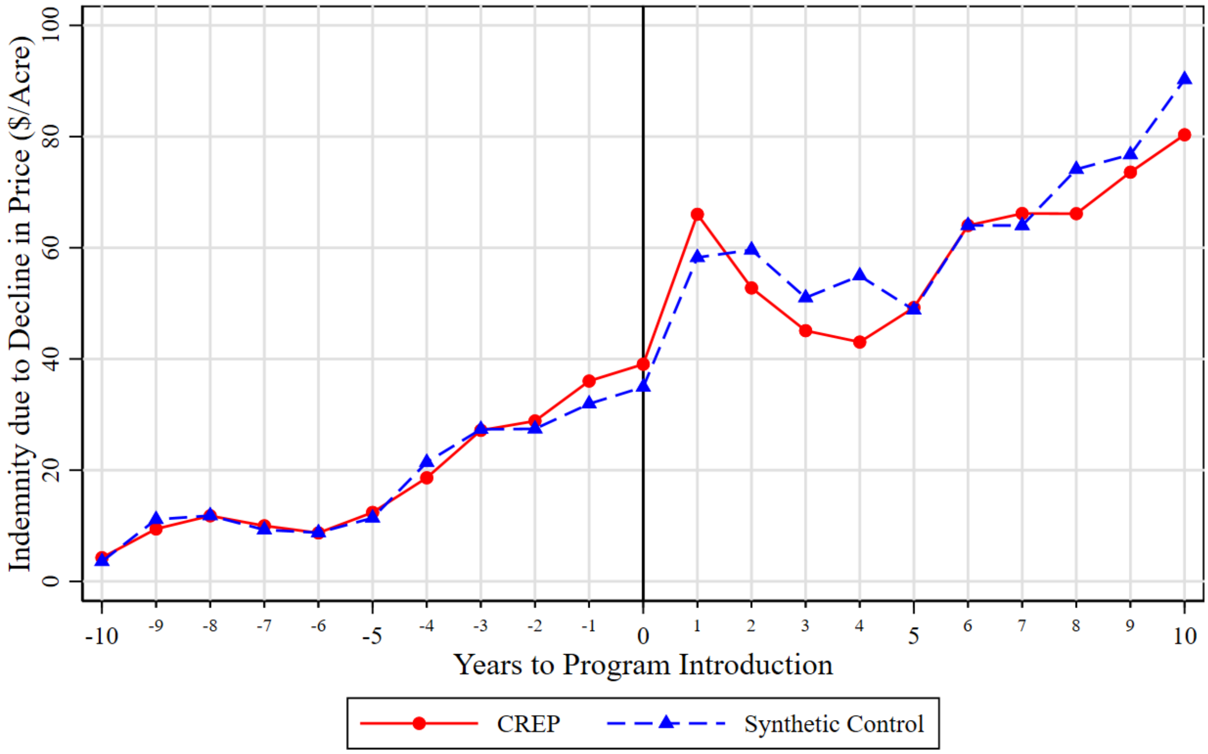


Pre-outcome Avg.: CREP 7314, Synthetic Control 10239, Pre-Diff. = -2925
Post-outcome Avg.: CREP 10418, Synthetic Control 14535, Post-Diff. = -4117
Unit of Obs.: County-by-Year
Num. of Obs.: 13056; 384 counties in year 1989-2022 (CREP Available 243, CREP N/A 141)

Note: The graph shows trends in county-level average acres enrolled under non-CREP Conservation Reserve Program (y-axis) over event time (x-axis) for both counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls.

Source: USDA-Farm Service Agency

Figure B6. Trends in Indemnity Payouts due to Decline in Crop Price

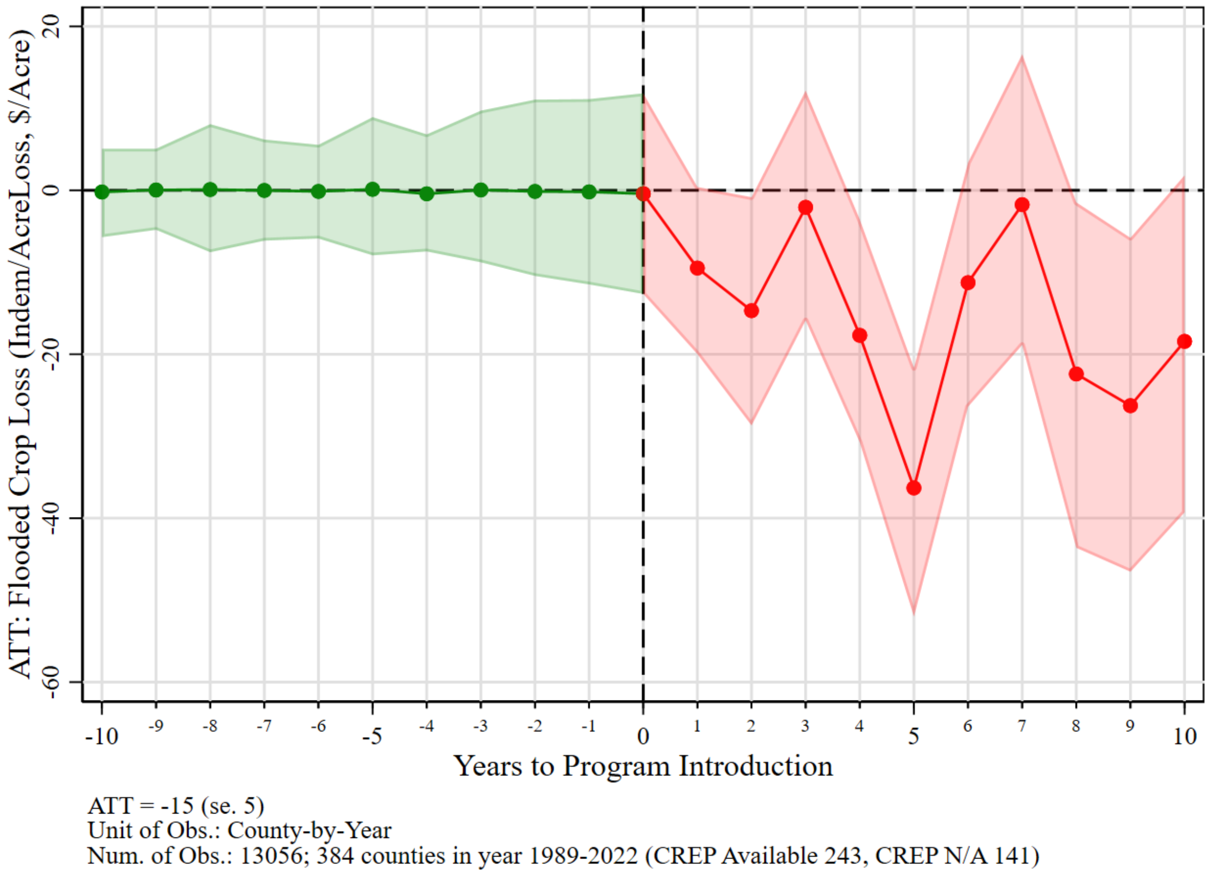


Pre-outcome Avg.: CREP 17, Synthetic Control 16, Pre-Diff. = 1
Post-outcome Avg.: CREP 59, Synthetic Control 62, Post-Diff. = -3
Unit of Obs.: County-by-Year
Num. of Obs.: 13056; 384 counties in year 1989-2022 (CREP Available 243, CREP N/A 141)

Note: The graph shows trends in county-level average indemnity payouts due to decline in crop price for acres insured under the federal crop insurance program (y-axis) across event time (x-axis) for both counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls.

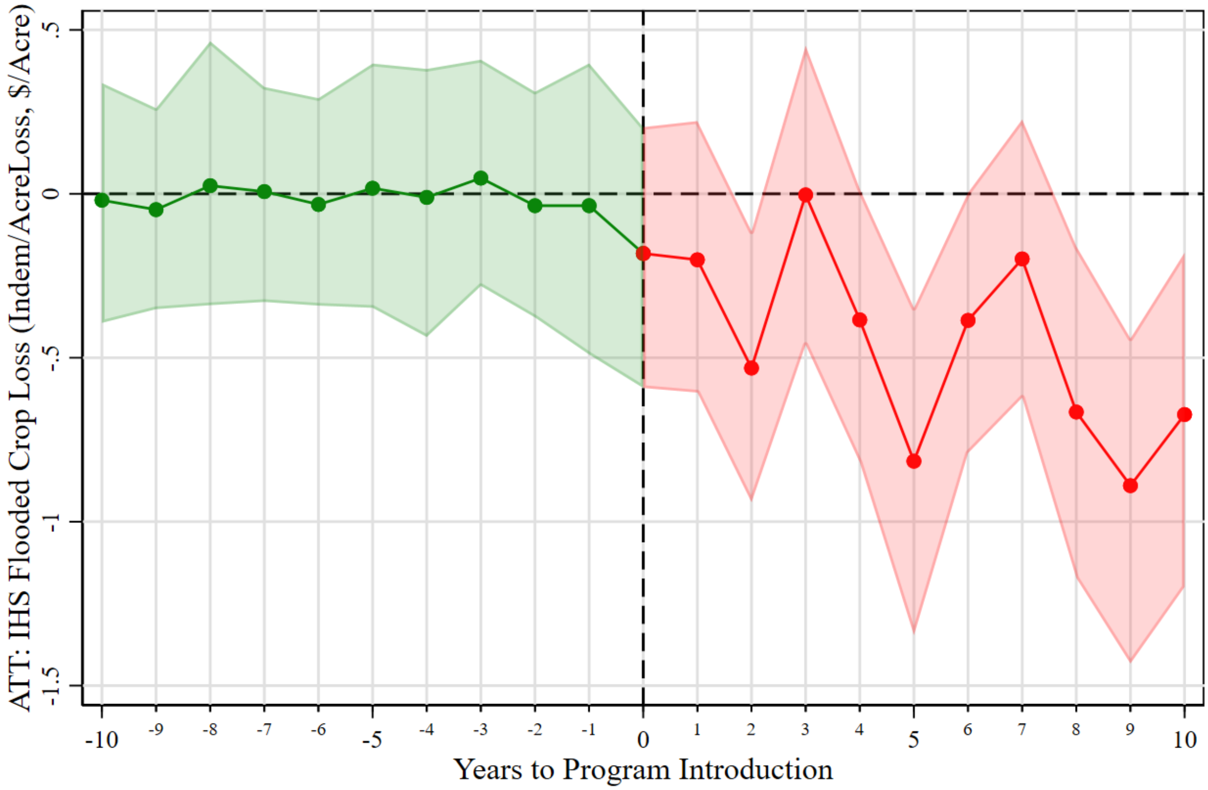
Source: USDA Risk Management Agency

Figure B7. Estimated Impact of CREP Introduction on Flooded Crop Damage (Outcome Only)



Note: The graph shows the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss (indemnity payouts per flooded crop acre, y-axis) across event time (x-axis) with 95 percent confidence intervals. The estimated average program effect is calculated by comparing the average change in crop loss relative to pre-policy average between counties with CREP and their synthetic controls. Only lagged outcomes are used in choosing weights of donor units to construct synthetic controls.

Figure B8. Estimated Impact of CREP Introduction on Flooded Crop Damage (IHS)



ATT = -.45 (se. .12)
Unit of Obs.: County-by-Year
Num. of Obs.: 13056; 384 counties in year 1989-2022 (CREP Available 243, CREP N/A 141)

Note: The graph shows the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss, measured by inverse hyperbolic sine (IHS) transformation of indemnity payouts per flooded acre (y-axis), across event time (x-axis) with 95 percent confidence intervals. The estimated average program effect is calculated by comparing the average change in crop loss relative to pre-policy average between counties with CREP and their synthetic controls. In addition to lagged outcomes, precipitation (mm) and growing degree days during the post-harvest (October to March) and crop growing seasons (April to September) are used as auxiliary covariates in choosing weights of donor units to construct synthetic controls.