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Abstract

Payments for ecosystem services (PES) programs can enhance resilience to extreme weather events by establishing natural infrastructure. I investigate the effectiveness of the Conservation Reserve Enhancement Program (CREP) in the United States in mitigating flooded crop losses through the restoration of riparian buffers and wetlands. By leveraging variation in the timing of the program's introduction across counties, I find that CREP reduced the number of flooded crop acres by 39 percent and the extent of damage on those acres by 26 percent during the initial 11 years of program implementation. The flood mitigation benefits of CREP also generated financial spillover effects on the federal crop insurance program, saving $94 million in indemnity payouts that would have otherwise been paid to insured farmers. Two-thirds of these benefits resulted from reduced flood damage on cropland in production, while the remaining benefits were attributed to the removal of at-risk cropland from production. The magnitude of benefits varied spatially and temporally depending on 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 in facilitating nature-based solutions for climate change adaptation.

Keywords: payments for ecosystem services, climate change adaptation, natural disasters, nature-based solutions, agri-environmental programs

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

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1. INTRODUCTION

Increasing extreme weather events associated with climate change incurs significant economic losses, resulting in substantial payments for disaster relief and crop insurance indemnities worldwide (Rosenzweig et al., 2002; Lobell et al., 2014; Carter et al., 2018; Ortiz-Bobea et al., 2021). To mitigate and adapt to climate change, current political efforts are increasingly focused on restoring nature-based infrastructure, such as forests and wetlands, which requires land use changes for existing agricultural land (e.g., the Biden-Harris Administration's Nature-Based Solution Roadmap at COP 27, the United Nations Decade on Ecosystem Restoration, and the World Bank Group's Climate Change Action Plan 2021-2025). Payments for ecosystem services (PES) programs play a major role in these efforts by offering financial incentives to farmers and landowners for adopting long-term conservation practices on their agricultural land.

PES programs have been widely implemented to address market failure in the provision of environmental services to society by sequestering carbon, reducing agricultural nonpoint source water pollution, and restoring wildlife habitat (see Jack et al., 2008; Alix-Garcia & Wolff, 2014; Ribaudo & Shortle, 2019; Wunder et al., 2020; Baylis et al., 2022 for reviews). In addition to the environmental benefits, there is evidence that establishing natural infrastructure can build resilience to extreme weather events, such as floods and droughts (Kousky & Walls, 2014; Michler et al., 2019; Taylor & Druckenmiller, 2022; Aglasan et al., 2023). For instance, the restoration of riparian buffers and wetlands can attenuate regional flood risks by absorbing excess water and slowing down the flow of floodwaters (Delgado et al., 2011; Acreman & Holden, 2013; Brody & Highfield, 2013; Croke et al., 2017). However, research on the cost-effectiveness of implementing PES programs for climate change adaptation remains limited.

I examine to what extent the introduction of PES programs mitigates economic losses under extreme weather events. My analysis focuses on the Conservation Reserve Enhancement Program (CREP) in the United States that has made significant investments in streambank and wetland restoration practices on agricultural land since its establishment in 1998. CREP has played a central role in reducing agricultural nonpoint source water pollution and restoring wildlife habitats, investing $1.6 billion on 1 million acres of agricultural land nationwide during 2013-2022 (USDA-FSA, 2023). The program converts environmentally sensitive cropland and marginal pastureland near water bodies into protective buffers and wetlands that are highly effective in filtering nutrient runoff and reducing regional flood risks.

I begin with a theoretical model describing two channels through which the introduction of PES programs can influence flood damage on cropland: (i) by removing at-risk cropland from production for conservation purposes (the "conversion effect") and (ii) by protecting remaining cropland in production from flooding through the establishment of natural infrastructure (the "protection effect"). Then, I estimate the impact of CREP introduction on crop losses due to flooding using county-by-year panel data obtained from administrative records. The estimated flood mitigation benefits of CREP are further decomposed into the relative contributions of the two channels described in the theoretical framework. Finally, I explore spatial and temporal heterogeneity of the estimated program benefits.

My empirical analysis exploits county-level spatial and temporal variation in the introduction of CREP and flood damage on cropland across 400 counties in the Mississippi River Basin from 1989 to 2022. The analysis utilizes administrative data obtained from the United States Department of Agriculture (USDA)'s Farm Service Agency (FSA) and Risk Management Agency (RMA). In an ideal experiment for assessing the flood mitigation benefits of CREP, we would compare flood damage on cropland between counties that are identical in all respects, 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 example, the government may implement CREP in regions vulnerable to frequent flooding on cropland, given the significant water quality benefits associated with retiring at-risk cropland. Second, the variation in the timing of CREP introduction across counties, along with potentially heterogeneous program effects, requires a careful selection of a comparison group in estimating causal effects. For instance, the conventional two-way fixed effects difference-in-differences (DID) estimator may introduce bias to the estimated program effect (Borusyak et al., 2021; Goodman-Bacon, 2021; Baker et al., 2022; Roth et al., 2023).

To address these challenges, my identification strategy leverages the staggered rollout of CREP across counties. In estimating the flood mitigation benefits of CREP, I consider two approaches for implementing DID with staggered program introduction: (i) a weighted average of DID estimates by the cohort of program adoption (de Chaisemartin & d'Haultfoeuille, 2020; Callaway & Sant'Anna, 2021; Sun & Abraham, 2021) and (ii) an average of county-specific DID estimates by leveraging the county-specific variation in the year of program introduction (Arkhangelsky et al., 2021; Ben-Michael et al., 2022). I implement the latter approach and construct a comparison group for each county with CREP availability using a synthetic control method (SCM) (Abadie & Gardeazabal, 2003; Abadie et al., 2010, 2015). The program effect estimator takes the form of a weighted DID estimator that constructs a counterfactual trend in flood damage for each county with CREP availability, using counties without CREP availability but exhibit similar *trends* in flood damage *prior to* the program's introduction. Thus, the estimator is robust to the presence of county-specific pre-policy trends in flood damage, a plausible scenario given the localized and catastrophic nature of flood events. The estimator also addresses bias derived from (i) unobserved time-invariant heterogeneity across counties, such as inherent production risks, and (ii) the program effect heterogeneity in the setting of staggered program adoption. To assess the robustness of the findings, I also estimate the program effect using the staggered DID estimator proposed by Callaway and Sant'Anna (2021).

Key identification assumptions include the absence of time-varying confounding factors, policy anticipation effects, and policy spillover effects. These assumptions are plausible in the context of this study for several reasons. First, the introduction of CREP to an individual county has been jointly determined by the federal and state governments to address their national environmental and resource concerns, such as declining wildlife habitat or nutrient pollution in the Gulf of Mexico, rather than specific trends in crop loss due to flooding in individual counties. Second, farmers have little incentive to manipulate or adjust their crop losses in anticipation of CREP availability, especially given the unpredictability of flood events and the program's stringent eligibility criteria. Third, I find little empirical evidence supporting inter-county spillover effects of the program.

I find economically and statistically significant flood mitigation benefits resulting from the introduction of CREP. Specifically, CREP reduced the number of flooded crop acres by 39 percent and mitigated the extent of crop damage on those acres by 26 percent during the initial 11 years of program implementation. The estimated program effects suggest that CREP protected 900,000 crop acres from flooding and saved $94 million (in 2022 USD) in indemnity payouts that would have been paid to the insured farmers in the absence of the program during the same period. Two-thirds of these benefits were attributed to the reduced flood damage on cropland in production, while the remaining benefits resulted from taking at-risk cropland out of production for conservation purposes.

The magnitude of flood mitigation benefits varies spatially and temporally depending on several factors. For example, the benefits generally increase with the duration of the program availability. The reduction in indemnity payouts per flooded crop acre starts at 20 percent during the initial five years of program implementation and increases to 29 percent during years six to eleven. The sources of this increase are twofold. First, the establishment of natural infrastructure on agricultural land increases as program participation rises over time. Second, the efficacy of restored riparian buffers and wetlands in mitigating flood damage may enhance over time as vegetation matures. I also find suggestive evidence that the flood mitigation benefits could be greater in counties that (i) are heavily dependent on crop insurance to manage production risk, (ii) are located further downstream where flood risk is inherently high, and (iii) have limited flood protection infrastructure, such as levees.

This study 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 (Lobell et al., 2014; Burke & Emerick, 2016; Ortiz-Bobea et al., 2018). This study demonstrates that the introduction of PES programs that establish nature-based infrastructure can play a pivotal role in mitigating crop losses under anticipated weather anomalies resulting from climate change. These findings align with ongoing global initiatives that utilize PES programs to restore natural ecosystems for climate change adaptation. In addition, the analysis has direct implications for managing flood risks in a major crop production region in the United States. To my knowledge, this is the first study on the adaptation benefits in agriculture associated with the introduction of CREP, which has spent billions of dollars in restoring natural infrastructure nationwide since 1998.

This study also contributes to a broader understanding of the interaction between existing government policies (Fischer & Preonas, 2010; Ifft et al., 2019; Fleming et al., 2020). Agricultural conservation programs and the federal crop insurance program accounted for two-thirds of projected expenditures allocated to farmers in the 2018 Farm Bill ($29 billion and $38 billion, respectively), excluding the Supplemental Nutrition Assistance Program (USDA-ERS, 2018). Thus, it is important for policymakers to comprehend the potential interaction between these two programs. Previous studies have mainly focused on whether the federal crop insurance program disincentives farmers to adopt loss mitigating strategies against weather anomalies (Mcleman &

Smit, 2006; Di Falco et al., 2014; Annan & Schlenker, 2015; Prokopy et al., 2019; Fleckenstein et al., 2020). In addition, they examine how heavily subsidized crop insurance affects agricultural conservation and environmental outcomes (Wu, 1999; Feng et al., 2013; Schoengold et al., 2015; Miao et al., 2016; Claassen et al., 2017; DeLay, 2019; Connor et al., 2021; Yu et al., 2022). This study examines the converse and shows that the introduction of PES programs may reduce production risks and improve the sustainability and financial performance of existing risk management programs, such as the crop insurance program.

Finally, this study has important implications for future research and existing policies. Existing analyses on the cost-effectiveness of PES programs have mainly compared additional environmental benefits to program payments (Ferraro & Simpson, 2002; Lichtenberg & Smith-Ramirez, 2011; Mezzatesta et al., 2013; Claassen et al., 2018; Fleming et al., 2018; Lichtenberg, 2021). In addition to the environmental benefits, future analyses should also consider (i) the long-term benefits of building resilience against adverse weather conditions and (ii) the economic spillover effects on disaster assistance programs. For instance, this study reveals that CREP's flood mitigation benefits in agriculture amount to 21 percent of the program expenditure, primarily driven by the protection services of established natural infrastructure. Similarly, prior research revealed spatial spillovers in the flood mitigation benefits associated with floodplain conservation and wetlands, extending to residential properties and cropland (Kousky and Walls, 2014; Karwowski, 2022; Taylor & Druckenmiller, 2022). Thus, incorporating these loss mitigating benefits would provide a comprehensive evaluation of PES programs, as weather anomalies and government-funded disaster payouts are expected to increase in the future (Tack et al., 2018; Reyes & Elias, 2019; Shirzaei et al., 2021; Bundy et al., 2022).

The remainder of this study is organized as follows. Section 2 provides background information on flood risk management, PES programs, and the federal crop insurance program. Section 3 introduces the theoretical framework that derives the underlying channels through which the introduction of PES programs can affect flood damage on cropland. Section 4 presents the data and explores the spatial and temporal variation in the introduction of CREP and flood damage on cropland across counties. Section 5 outlines the empirical framework, focusing on the identification strategy that reveals the flood mitigation benefits of CREP. Section 6 and 7 discuss the empirical findings, followed by falsification tests, sensitivity checks, and heterogeneity analysis. Section 8 concludes with a summary of the findings and policy suggestions.

2. BACKGROUND AND INSTITUTIONAL CONTEXT

2.1 Flood Risk Management: Gray 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). The Mississippi River Basin has experienced an increasing frequency of major floods, including destructive flood events in 1927, 1969, 1979, 1982, 1993, 2005, 2011, and 2019.[1] For example, the 1993 flood in the upper Mississippi River Basin inundated over 6.6 million acres across 419 counties in the Midwest, resulting in estimated damages of $12 billion to $16 billion, with agriculture accounting for over half of these costs (Galloway, 1995). Most recently, 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 "gray" infrastructure such as levees and dams managed by the U.S. Army Corps of Engineers, especially in the lower Mississippi River Basin (Galloway, 1995; Carter et al., 2019; Bradt & Aldy, 2022). 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 nature-based solutions for flood risk management. Riparian buffers are natural vegetation such as trees and grasslands 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 habitats, they also slow down floodwaters and shorten flood durations, thereby mitigating flood risks for adjacent cropland (Acreman & Holden, 2013; Kousky et al., 2013; Kousky & Walls, 2014; Mason-McLean, 2020).

[1] An overview of historical flood events in the Mississippi River Basin, including their impacts, is available at: https://www.weather.gov/media/jan/JAN/Hydro/Flood_History_MS.pdf

2.2 Payments for Ecosystem Services Program

The voluntary restoration of those natural infrastructures by farmers and landowners has been limited due to several reasons (see Prokopy et al. (2019) for a review). First, landowners may be less aware of the private benefits of conservation because existing empirical evidence has been focused on off-site public environmental benefits, rather than on-site private benefits. Second, landowners 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 (Di Falco et al., 2014; Annan & Schlenker, 2015; Claassen et al., 2017; Connor et al., 2021).

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, and wetland conversion. 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 the 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 upfront 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 is 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 convert agricultural land into conservation cover to address environmental and resource concerns at the state, regional, and national levels. For example, CREP in the Mississippi River Basin aims to restore filter strips, riparian buffers, and wetlands in the major tributaries of Mississippi River (e.g., IA, IL, MN, and OH) to reduce agricultural nonpoint source water pollution in the Gulf of Mexico and restore wildlife habitats. Since 1998, CREP has been introduced to selected groups of counties in 32 states. In the fiscal year of 2022, CREP allocated $154 million in annual payments to establish and maintain approximately 800,000 acres of conservation practices on agricultural land (USDA-FSA, 2023).

The introduction of CREP to a specific county or watershed requires collaboration between the partners (local and state government) and the federal government. The partners or the federal government first identify the environmental and resource concerns that can be addressed through the implementation of CREP. The federal agency then reviews and evaluates proposed conservation practices supported by CREP and their impacts on the local community in accordance with the requirements of the National Environmental Policy Act. 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 restore filter strips, riparian buffers, and wetlands on their eligible land in exchange for program payments. To qualify as cropland for CREP, the land must be environmentally sensitive (e.g., located adjacent to stream and water bodies) 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. These eligibility criteria likely exclude cropland with a high risk of loss and reduce farmer’s incentive to change cropping behavior in anticipation of the program availability.

Financial incentives in CREP include both one-time upfront payment and fixed annual payments throughout the contract lifetime. CREP offers cost-share assistance that covers 50 to 100 percent of the installation costs and fixed annual payments to compensate for the land rental rate and the maintenance costs of the installed practices. These annual program payments are designed to be competitive, typically ranging from 150 to 300 percent of the county's soil rental rate in the year of program participation, which is published by USDA's National Agricultural Statistics Service. The annual payment is further adjusted within counties based on soil types and productivity, using the national commodity crop productivity index published by the USDA's NRCS. Some states also offer additional 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 date 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. Overall, CREP offers competitive payments and enforces strict non-compliance penalties, which contributes to the change in regional landscape over the medium to long term as the program becomes available to landowners.

Previous research indicates that farmers and landowners may have adopted conservation practices even without the financial incentives provided by the PES program, suggesting imperfect additionality (Chambers, 1992; Wu & Babcock, 1996; Ferraro & Simpson, 2002; Ferraro, 2008; Lichtenberg & Smith-Ramirez, 2011; Mezzatesta et al., 2013; Fleming, 2017; Fleming et al., 2018; Lichtenberg, 2021). In such instances, the introduction of PES programs may not lead to an overall increase in the adoption of conservation practices. However, the additionality of U.S. federal PES programs tends to be higher for land use conversion practices, such as the 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).

2.4 Crop Loss Covered under the Federal Crop Insurance Program

In addition to the agri-environmental programs, the federal government also heavily subsidizes crop insurance program to help farmers manage risks associated with crop yield and revenue losses caused by weather and market conditions, such as drought, flood, and decline in crop price. In the event of yield or revenue losses covered by the insurance plan, farmers receive indemnity payments as monetary compensation. These payments are calculated based on the difference between guaranteed and actual (realized) yield or revenue. Most crop insurance plans establish either guaranteed yield or revenue by using approved Actual Production History, 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).

For yield protection, the guaranteed yield is determined by multiplying the Actual Production History 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 and harvest prices obtained from the futures market. In the case of revenue protection, the guaranteed revenue is calculated by multiplying the Actual Production History, 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 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.[2] 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 caused by a water deficit or surplus, such as drought, excessive precipitation,

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

or floods during the period from 2001 to 2016 (Reyes et al., 2020; Reyes & Elias, 2019). Specifically, crop losses due to flooding were concentrated in the Mississippi River Basin during the early growing season, from April to July (Bundy et al., 2022).

3. THEORETICAL FRAMEWORK

This section presents a theoretical framework to analyze how the introduction of a PES program can enhance climate change adaptation in agriculture by incentivizing the adoption of conservation practices. The framework employs a static model in which a risk-averse farmer maximizes expected utility by (i) allocating land between crop production and conservation and (ii) adjusting the coverage level of crop insurance for cropland in production. The theoretical analysis serves several purposes. First, it demonstrates how PES program payments influence the farmer's optimal land use decisions, reallocating land from crop production to conservation. Second, it identifies two mechanisms through which PES programs reduce crop losses: (i) by converting at-risk cropland into conservation, thereby eliminating potential losses (the conversion effect), and (ii) by reducing the extent of damage on remaining cropland through the protective services provided by natural infrastructure (the protection effect). Third, the framework highlights financial spillover effects, as PES programs reduce indemnity payouts from crop insurance by mitigating weather-related risks. Finally, it predicts potential heterogeneity in the loss mitigating benefits of PES programs across different regions and contexts.

The theoretical framework relies on several simplifying assumptions. First, it assumes that farmers operate independently, making decisions about land use allocation and crop insurance based on individual preferences, land characteristics, and policy parameters, without accounting for interactions or cooperative behavior among neighboring farmers. Second, the framework explicitly incorporates within-farm spillover effects, where conservation practices in one area of the farm provide benefits to other areas, such as mitigating flood damage. However, cross-farm spillover effects are not explicitly modeled and are instead implicitly embedded in parameters like flood damage severity and conservation effectiveness. Third, conservation acreage and insurance coverage are treated as endogenous variables determined by the farmer's decision-making process, while other parameters, such as flood risk, conservation costs, PES payments, and insurance premiums, are treated as exogenous and fixed based on environmental conditions, or intrinsic characteristics of the land. Finally, the framework adopts a static structure, excluding dynamic adjustments or long-term strategies. These assumptions simplify the analysis, enhance the model's tractability, and facilitate a focused examination of the core farm-level mechanisms through which PES programs influence crop losses and insurance payouts.

3.1 Farmer's Land Use Decision

Consider a farmer whose risk preference is characterized by constant absolute risk aversion.[3] The farmer allocates a fixed total cropland L into two portions: e acres for conservation practices and $L - e$ acres for crop production with crop insurance.[4] In the case of crop production, the farmer faces two possible states of nature. Under normal weather conditions (the "good state"), crop production yields an expected net return of y per acre. On the other hand, cropland is susceptible to flooding (the "bad state") with a likelihood $q > 0$, resulting in a reduction of net crop return y by an amount D where $0 < D \leq y$. In the event of flood-induced crop loss, an insurance policy covers a fraction β (where $0 \leq \beta \leq 1$) of the total damage, leading to an indemnity payout of βD, with the farmer bearing the remaining fraction $(1 - \beta)D$. The crop insurance policy premium equals the expected indemnity payout with a markup factor m, $mq\beta D$, where the premium is actuarially fair when $m = 1$.

The farmer can choose to allocate some of that cropland to conservation cover at a per-acre cost c and obtain private benefits w, such as erosion protection, recreational and scenic amenities, satisfaction from stewardship, along with per-acre monetary compensation $r > 0$ from a PES program. These private benefits of conservation $w + r$ remain constant regardless of the states of nature (e.g., weather conditions). In addition, the conservation acreage e mitigates the extent of loss D on the remaining cropland $L - e$ under the bad state with a diminishing effect, $\frac{\partial D}{\partial e} \equiv D_e < 0$ and $\frac{\partial^2 D}{\partial e^2} \equiv D_{ee} > 0$.

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[3] For simplicity, the model omits explicit subscripts (i) for individual farmers and focuses on general mechanisms but implicitly accounts for heterogeneity in parameters.

[4] The fixed total cropland L excludes the possibility of the farmer expanding their overall crop acreage in response to the introduction of CREP. Previous studies have suggested that conservation subsidies on cropland might lead to an increase in the total cropland under production, a phenomenon often referred to as "slippage" (Wu, 2000; Lichtenberg & Smith-Ramirez, 2011; Pfaff & Robalino, 2017; Fleming et al., 2018). However, CREP enrollment would not significantly increase cropland acreage elsewhere because the program targets cropland adjacent to waterbodies with environmental concerns, which is likely a small portion of farm. In addition, CREP payment is only eligible for cropland with cropping history, which reduces farmer's incentive to produce crop on previously uncultivated land for program payment.

Let π_1 and π_0 represent the total land use return from cropland L under the bad state and good state, respectively. Then, the risk-averse farmer chooses the conservation acreage e and the coverage level β to maximize expected utility V, considering the two possible states of nature:

$$\max_{e,\beta} V \equiv qU(\pi_1) + (1-q)U(\pi_0)\,, \tag{1}$$

where:

$$\pi_1 = \underbrace{[y-(1-\beta)D - mq\beta D](L-e)}_{\text{net crop return -- bad state}} + \underbrace{(w+r-c)e}_{\text{net return from conservation}},$$

and:

$$\pi_0 = \underbrace{[y - mq\beta D](L-e)}_{\text{net crop return -- good state}} + (w+r-c)e.$$

The optimal coverage level β^* satisfies the following first-order necessary condition:

$$\frac{\partial V}{\partial \beta} \equiv qD(L-e)U'(\pi_1) \leq mqD(L-e)[qU'(\pi_1) + (1-q)U'(\pi_0)]. \tag{2}$$

Given that $U'(\cdot) > 0$, $U''(\cdot) < 0$, and $U'(\pi_1) > U'(\pi_0)$, the farmer would increase insurance coverage on crop loss as long as the marginal utility gained from higher indemnity payouts under the bad state on the left-hand side outweighs that from higher premium costs in both states on the right-hand side. If the premium is actuarially fair or subsidized ($m \leq 1$), then the farmer would fully insure crop loss under the bad state ($\beta = 1$) at any conservation acreage e because the marginal utility of income under the bad state always outweighs that under the good state for all e (i.e., $U'(\pi_1) \geq m[qU'(\pi_1) + (1-q)U'(\pi_0)]\ \forall e$). In fact, the federal crop insurance program heavily subsidizes crop insurance ($m < 1$), so full insurance would be optimal for the farmer. However, the federal crop insurance program imposes restrictions on loss coverage, capping it at less than full insurance ($\beta < 1$). Thus, the farmer's optimal coverage level β^* is fixed at the maximum attainable level allowed by the program at any conservation acreage e.

The optimal conservation acreage e^* satisfies the following first-order necessary condition:

$$\frac{\partial V}{\partial e} \equiv [qU'(\pi_1) + (1-q)U'(\pi_0)]\left\{\begin{matrix} \underbrace{-(y - mq\beta^* D)}_{\text{foregone net crop return and insurance premium}} \\ +\underbrace{w+r-c}_{\text{net return from conservation}} \\ -\underbrace{mq\beta^* D_e(L-e^*)}_{\text{reduced insurance premium for remaining cropland}} \end{matrix}\right\} \tag{3}$$

$$\underbrace{+qU'(\pi_1)(1-\beta^*)[D - D_e(L-e^*)]}_{\text{loss mitigating benefits of conservation practice}} \leq 0.$$

The optimal allocation of conservation acreage e^* balances the marginal utility from crop production and that from the adoption of conservation practice. Expanding conservation acreage would entail the loss of net crop return y but increase net return from conservation $w + r - c$ and reduce expenditure on insurance premiums, $mq\beta^*[D(e^*) - D_e(L - e^*)]$. The additional conservation acreage would also contribute to mitigating crop loss in the bad state $q(1 - \beta^*)[D(e^*) - D_e(L - e^*)]$.

3.2 Establishing Natural Infrastructure Through PES Programs

It is straightforward to show that additional financial incentives r offered by the PES program encourage the farmer to adopt a conservation practice. The impact of receiving the program payment r on the optimal conservation acreage e^* is:

$$\frac{\partial e^*}{\partial r} \equiv -\frac{\frac{\partial^2 V}{\partial e\,\partial r}}{\frac{\partial^2 V}{\partial e^2}} \geq 0. \tag{4a}$$

because

$$\frac{\partial^2 V}{\partial e\,\partial r} \equiv -\phi\underbrace{\left[qU'(\pi_1)\frac{\partial \pi_1}{\partial e} + (1-q)U'(\pi_0)\frac{\partial \pi_0}{\partial e}\right]}_{=0\text{ (first-order condition for } e)} e^* + qU'(\pi_1) + (1-q)U'(\pi_0) \geq 0, \tag{4b}$$

where ϕ is the farmer's coefficient of constant absolute risk aversion (i.e., $-\phi U'(\cdot) = U''(\cdot)$). The denominator on the right-hand side represents the concavity of the farmer's objective function V with respect to conservation acreage e:

$$\frac{\partial^2 V}{\partial e^2} \equiv q\left[U''(\pi_1)\left(\frac{\partial \pi_1}{\partial e}\right)^2 + U'(\pi_1)\frac{\partial^2 \pi_1}{\partial e^2}\right] + (1-q)\left[U''(\pi_0)\left(\frac{\partial \pi_0}{\partial e}\right)^2 + U'(\pi_0)\frac{\partial^2 \pi_0}{\partial e^2}\right] \leq 0, \tag{4c}$$

because:

$$\frac{\partial^2 \pi_1}{\partial e^2} \equiv [-(1-\beta)D_{ee} - m\beta q D_{ee}](L - e^*) - 2[-(1-\beta)D_e - m\beta q D_e] \leq 0, \tag{4d}$$

and:

$$\frac{\partial^2 \pi_0}{\partial e^2} \equiv -m\beta q D_{ee}(L - e^*) + 2m\beta q D_e \leq 0. \tag{4e}$$

3.3 Loss Mitigating Benefits of PES Programs

Now, I show that introducing PES program payments r reduce the expected crop loss, $qD(e^*)(L-e^*)$, through two channels:

$$\frac{\partial qD(e^*)(L-e^*)}{\partial r} \equiv \frac{\partial e^*}{\partial r}\left[\underbrace{-qD(e^*)}_{\text{conversion effect}} + \underbrace{qD_e(L-e^*)}_{\text{protection effect}}\right] \leq 0, \tag{5}$$

because $\frac{\partial e^*}{\partial r} \geq 0$ as shown above and $D_e < 0$ supported by the existing literature. Condition (5) reveals two potential channels through which the introduction of PES programs reduces crop loss. First, the PES program eliminates the risk of potential crop loss $qD(e^*)$ by converting at-risk cropland into conservation use (the conversion effect). Second, the PES program reduces the extent of potential loss on the remaining cropland in production $qD_e(L-e^*)$ as the established natural infrastructure on conservation acreage provides ecosystem services, such as flood control, enhancing the resilience of cropland in production (the protection effect).

Given that the crop insurance policy covers a fixed portion (β^*) of crop loss, PES program payments also influence insurance indemnity payouts. A linear approximation of the change in the expected crop loss, measured through insurance claims with a chosen coverage level of loss β^*, can be written as:

$$\beta^*\Delta qD(e^*)(L-e^*) \approx [-\beta^* qD(e^*) + \beta^* qD_e(L-e^*)]\frac{\partial e^*}{\partial r}\Delta r \leq 0. \tag{6}$$

Equation (6) shows how PES programs indirectly reduce the expected indemnity payouts from crop insurance program. As shown in equation (5), the reduction is driven by two channels: the conversion effect, which decreases the cropland area exposed to potential damage, and the protection effect, which mitigates the damage on remaining cropland. Together, these mechanisms reduce overall crop losses, translating into lower expected indemnity payouts for insured cropland. Thus, I have:

Proposition. *The introduction of PES programs reduces insurance indemnity payouts by establishing natural infrastructure that mitigates crop loss caused by extreme weather shocks.*

Equation (6) also implies that the magnitude of loss mitigating benefits of PES programs would be heterogeneous across farmers depending on weather risk (q), the extent of crop loss under extreme weather events (D), the effectiveness of conservation practices in mitigating crop loss (D_e), crop insurance coverage levels (β^*), the additional conservation acreage induced by PES program payments $\left(\frac{\partial e^*}{\partial r}\Delta r \equiv \Delta e^*\right)$, and the cropland acreage remaining in production that is protected by the established natural infrastructure and crop insurance policies $(L - e^*)$.

Spatially, the introduction of PES programs in regions with higher weather-related risks is expected to yield greater reductions in crop loss and insurance indemnity payouts. For example, in flood-prone areas such as the downstream regions of the Mississippi River Basin, reallocating cropland to conservation under PES programs is likely to significantly reduce crop loss and associated indemnity payouts. Conversely, in areas with lower flood risks, the conversion effect is expected to be smaller. The protection effect also varies geographically depending on the effectiveness of conservation practices in mitigating crop damage. In regions where engineered flood controls, such as levees, are already in place, the additional benefits provided by natural infrastructure may be limited. Furthermore, regions with higher participation in PES programs and crop insurance coverage levels are expected to experience greater reductions in indemnity payouts, holding other factors constant.

Overall, the theoretical analysis suggests that PES programs can reduce crop losses and insurance indemnity payouts, with the magnitude of these benefits likely varying across farmers. To test these predictions, the empirical analysis estimates the flood mitigation benefits of CREP and examines their spatial and temporal heterogeneity across key factors discussed above. Due to the unavailability of farm-level panel data linking conservation practices, crop insurance, and location, the study uses county-level administrative data, enabling a broader geographical and temporal scope for the analysis. The theoretical framework provides insight into the farm-level mechanisms driving county-level impacts observed in the empirical analysis. While the theoretical model focuses on individual farmer behavior, the empirical analysis captures the cumulative effects at the county level by using aggregated measures such as total conservation acreage, flood damages, and insurance payouts to evaluate the overall impact of PES programs. Thus, the empirical analysis tests theoretical predictions while acknowledging the limitations of aggregation and unobserved farm-level heterogeneity. The following section details the data used in the empirical analysis.

4. DATA

To estimate the flood mitigation benefits of CREP, I use administrative records from the USDA's RMA and FSA and construct county-by-year panel data on (i) flooded crop loss covered under the federal crop insurance program and (ii) the availability of CREP, acres enrolled, and program payments from 1989 to 2022. My analysis focuses on (i) 250 counties where CREP was introduced between 1998 and 2011 and (ii) 150 counties where CREP was never available until 2022. These counties are distributed across 13 states within two farm resource regions in the Mississippi River Basin: Heartland and Mississippi River Portal regions.[5] These regions are characterized by extensive crop production in the presence of flood risk because of their proximity to major tributaries of the Mississippi River, such as the Missouri River, Ohio River, and Arkansas River. The analysis only includes counties with crop acres insured under the federal crop insurance program before the introduction of CREP.

A county-level analysis provides several advantages when assessing the flood mitigation benefits of CREP. First, CREP likely alters regional landscape through the 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. Finally, conducting a county-level analysis allows for a broader spatial and temporal scope of the study that covers major crop production regions in the United States over the past 34 years.

In the following subsections, I provide detailed information about the county-level panel data on CREP availability and participation (Section 4.1), flooded crop loss covered under the federal crop insurance program (Section 4.2), and weather information used in estimating the program effect (Section 4.3). Table 1 presents the average values of variables used in the main analysis for counties where CREP was introduced in any year after 1997 and counties where CREP was not available until 2022.

[5] These regions are defined by the USDA's Economic Research Service based on similar agricultural production practices, soil types, and climate conditions. A map of farm resource regions is available at: https://www.ers.usda.gov/publications/pub-details/?pubid=42299.

Table 1. Descriptive Statistics: Main Analysis

Time Period (Year)	1989-1997		1998-2022	
County: CREP introduction in any year post-1997	Yes	No	Yes	No
Panel A. Conservation Reserve Enhancement Program (CREP)		Mean		
Number of acres enrolled	N/A	N/A	974.6	N/A
Annual program payments ($1,000s)	N/A	N/A	201.0	N/A
Panel B. Flood Damage on Cropland				
Indemnity payouts per flooded crop acre ($/acre)	60.9	57.1	80.2	99.6
Indemnity payouts for flood damage ($1,000s)	50.5	72.8	79.8	193.2
Crop acres flooded	375.8	469.6	338.2	666.6
Panel C. Federal Crop Insurance Program Participation				
Crop acres insured (1,000s)	108.2	85.2	185.7	155.7
Coverage level insured (%, area-weighted)	64.4	63.8	73.9	70.7
Panel D. Weather Conditions				
Total Precipitation (mm)				
Post-harvest (Oct-Mar)	355.6	449.1	359.9	437.4
Growing season (Apr-Sept)	632.0	661.7	630.2	652.8
Growing degree days (10-29 Celsius)				
Post-harvest (Oct-Mar)	193.5	277.7	216.9	302.8
Growing season (Apr-Sept)	1,627.4	1,798.8	1,735.9	1,907.2
Number of counties	250	150	250	150
Number of observation (county-by-year)	2,250	1,350	6,250	3,750

Notes: The table presents average values of variables used in the main analysis for 250 counties that CREP became available between 1998 and 2011 and 150 counties that CREP was not available during the analysis period. All monetary values are in 2022 USD. *Source*: USDA Risk Management Agency and Farm Service Agency, and Schlenker and Roberts (2009).

4.1 Conservation Reserve Enhancement Program

The USDA's FSA provides county-by-year panel data on CREP availability and participation from 1998, the first year of CREP, to 2022. CREP became available in a county when landowners have the opportunity to receive payments from the program in return for establishing or maintaining conservation practices. The county participates in CREP when landowners choose to enroll their land in the program and commit to adopting and maintaining conservation practices as specified in their CREP contract. Thus, 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

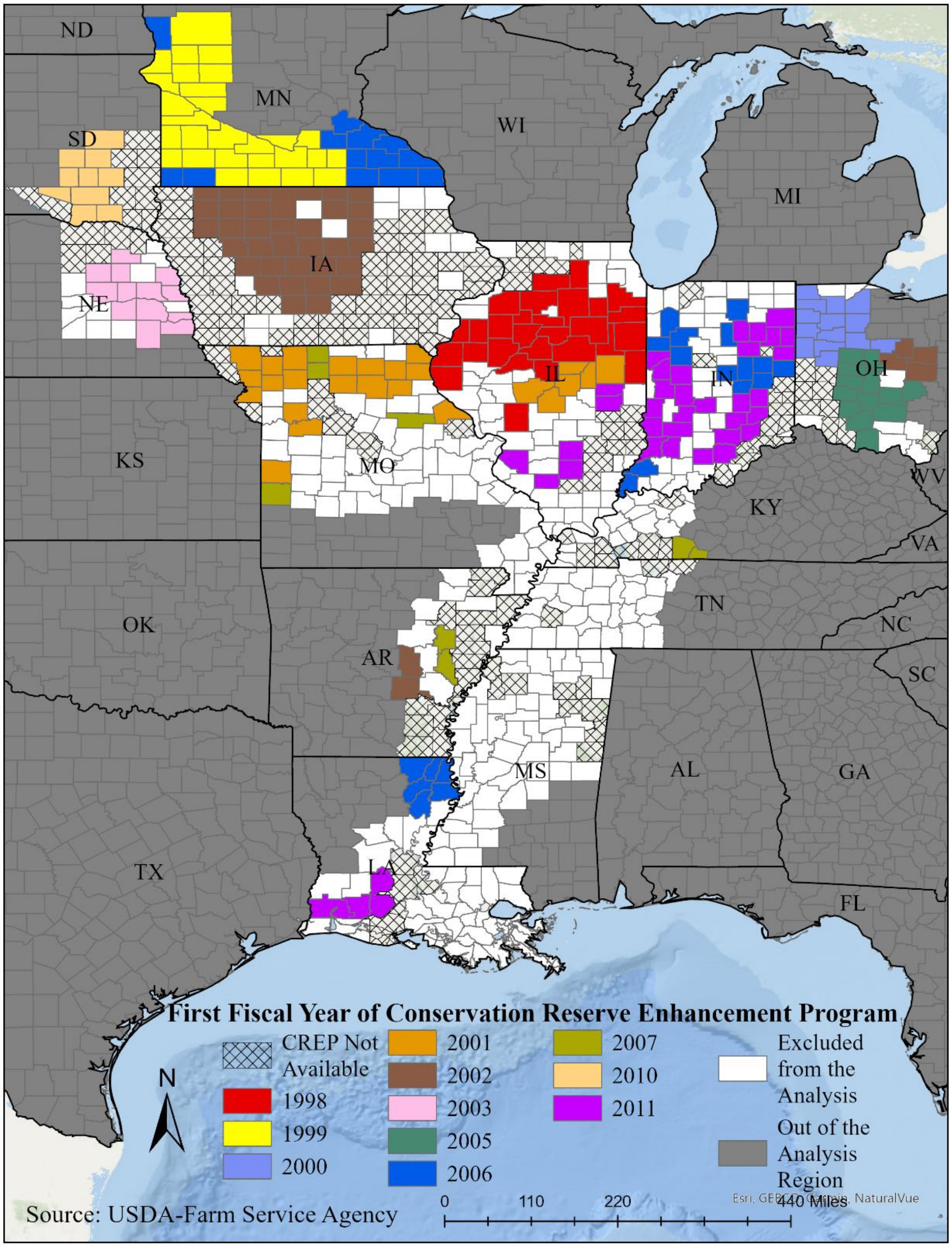


Figure 1. Spatial and Temporal Variation in the Introduction of CREP: Heartland and Mississippi River Portal Regions

Notes: The figure shows a map of counties in the analysis with spatial and temporal variation in the timing of CREP's introduction across counties. Out of a total of 709 counties in the Heartland and Mississippi River Portal regions, the analysis includes 250 counties with CREP, which had insured crop acres from 1998 to the year of CREP introduction, and 150 counties without CREP, which had insured crop acres from 1998 to 2011.

encompasses the period from October 1997 to September 1998. If CREP is introduced in the fiscal year of 1998, the conservation practices installed through CREP may provide protection services to neighboring cropland starting in the subsequent crop year of 1998. Therefore, I match crop loss data in crop year of 1998 with CREP data in the fiscal year of 1998 to construct the county-by-year panel data set.

The data set consists of (i) 250 counties where CREP was introduced between 1998 and 2011 and had insured crop acres between 1989 and the year of CREP introduction, and (ii) 150 counties where CREP was never available until 2022 and had insured crop acres between 1989 and 2011. Figure 1 presents a map that summarizes spatial and temporal variation in the timing of CREP availability across counties included in the analysis. CREP availability varies spatially and temporally even within the same state as the partnership may prioritize a specific watershed region to address environmental concerns and then subsequently expand the program to other regions with similar or different environmental and resource concerns. For instance, in 2005 (FY 2006) the Indiana State Department of Agriculture partnered with USDA's FSA and introduced CREP to counties in three watersheds to reduce agricultural nonpoint source pollution and restore wildlife habitats through the 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, such as foregone crop return of program eligible agricultural land, may vary across farms and crop year. Other factors, such as crop market conditions, land ownership, age, risk preference, and education, can also influence the landowner's decision to participate in CREP (Lynch & Brown, 2000; Lichtenberg, 2004, 2007; Prokopy et al., 2019). Figure 2 provides an overview of timing variation in the CREP availability and participation across counties included in the analysis.[6]

Figure 3 presents an overview of the county-level average acreage enrolled in CREP by practice type and the program payments in 250 counties with CREP by the duration of program availability. During the initial 11 years of the CREP implementation, the government invested a total of $622 million (in 2022$, CPI-adjusted) to establish and maintain approximately 380,000

[6] See Table A1 in Appendix A for a more detailed breakdown of the number of counties by state and their CREP availability and participation.

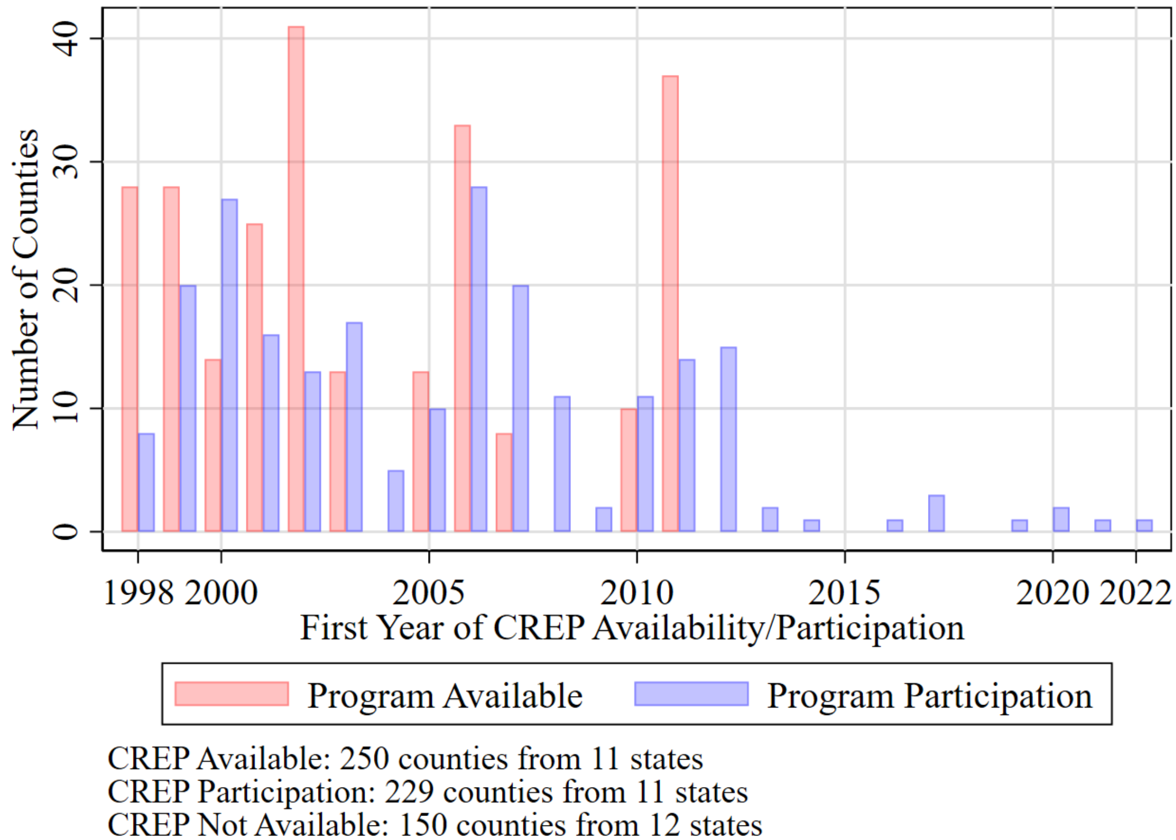


Figure 2. Conservation Reserve Enhancement Program: Timing Variation of Introduction and Participation across Counties, 1998-2022

Notes: The graph shows the number of counties that introduced Conservation Reserve Enhancement Program (CREP) in any year before 2012 (y-axis) by the initial fiscal year of CREP availability (red) or participation (blue) (x-axis). Among 400 counties included in the analysis, the CREP has become available to 250 counties at different timings since 1998 (program available). By the year 2022, 229 of these counties had enrolled crop acres in the program to establish conservation practice (program participation). *Source*: USDA Farm Service Agency.

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 habitats. Roughly 50 percent of total acres of conservation practices installed through CREP are riparian buffers, wetlands, and filter strips. Likewise, the restoration of wildlife habitats via vegetative buffers and conservation cover along the water bodies also accounts for 32 percent of total enrolled acres. The remainder of the conservation practices installed includes grass and tree plantings. According to the USDA's NRCS Conservation Practice Physical Effects and scientific literature, these

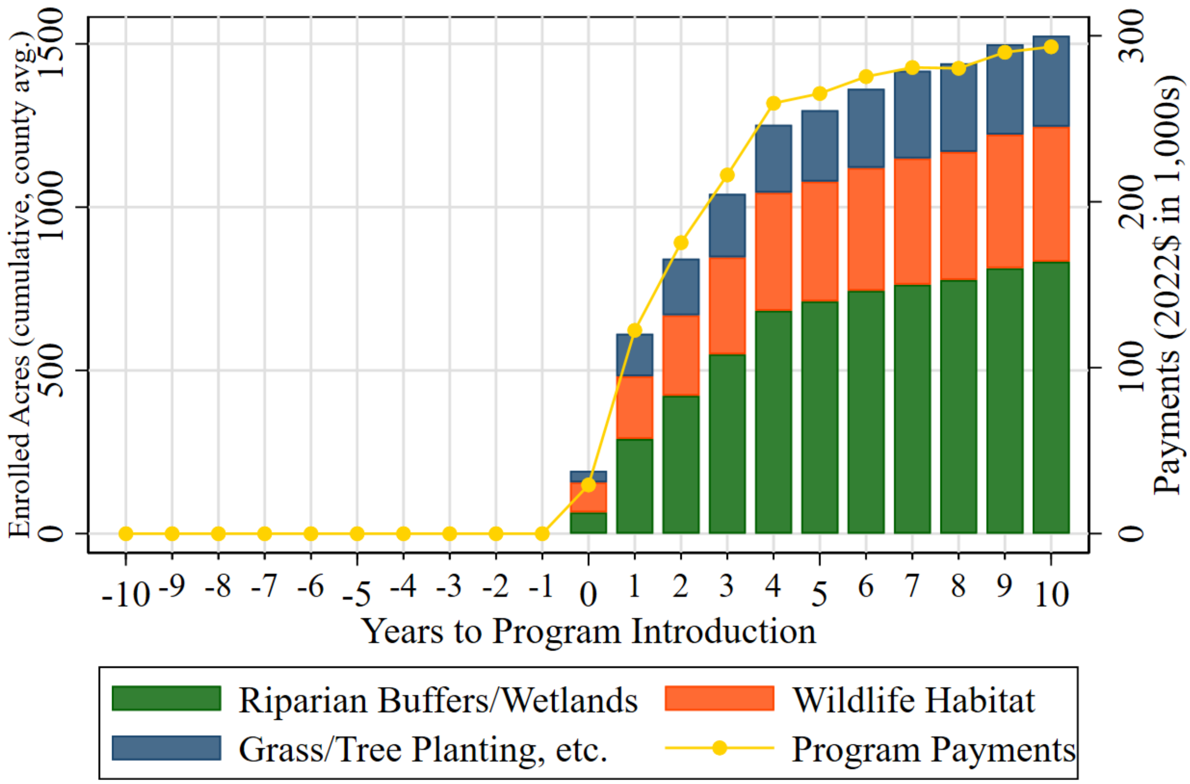


Figure 3. Conservation Reserve Enhancement Program: Enrolled Acres and Program Spending by Event Time

Notes: 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 2022$), for 250 counties with CREP availability in Heartland and Mississippi River Portal regions. The x-axis represents the length of exposure to the program availability (event time). *Source*: USDA Farm Service Agency.

conservation practices directly and indirectly mitigate flood risk on neighboring cropland by enhancing streambanks and addressing seasonal high water, ponding, and flooding (Darby, 1999; Acreman & Holden, 2013; Mason-McLean, 2020).

There are two caveats in interpreting the program enrollment data. First, the program payment data only includes annual payments and excludes other types of payments, such as cost-share payments, understating the total program costs. Second, the program data offers cumulative acres enrolled in the program, which is the sum of previously enrolled and newly enrolled acres less contract-expired acres. Given that most CREP contracts for land use conversion practices span at least a decade, the analysis primarily focuses on the initial 11 years of program availability including the year of program introduction. This approach addresses concerns related to (i) underestimating the total acreage dedicated to conservation practices through CREP due to contract expiration and (ii) potential reversals in program availability after a decade of implementation.

In the setting of staggered policy rollout, a panel data set that is balanced in calendar time becomes unbalanced in event time (duration after the policy onset) due to variation in the timing of policy adoption across counties. Thus, 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 focuses on counties with at least 11 years of exposure to the program availability, including the year of program introduction. Out of 709 counties within the analysis region, eleven counties in Mississippi are dropped because CREP first became available in these counties in 2016.

4.2 Flood Damage on Cropland

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, cause of loss, and coverage level, from 1989 to 2022. To measure the extent of crop damage due to flooding, I use the ratio of indemnity payouts for flooded crop loss (in 2022$, CPI-adjusted) to the total number of flooded crop acres reported in the federal crop insurance program. I also use indemnity payouts per liability (loss cost) as a robustness check. These measures of crop loss have been extensively used in the analysis of crop losses and actuarial assessments of the federal crop insurance program (Glauber, 2004; Woodard et al., 2011, 2012; Coble & Barnett, 2013; Goodwin & Piggott, 2020; Perry et al., 2020; Bundy et al., 2022). I aggregate the flooded crop loss to the county-by-year level, including all insurance plans with coverage level and eight major crops (corn, soybeans, wheat, rice, cotton, barley, oats, and grain sorghum) from 1989 to 2022.

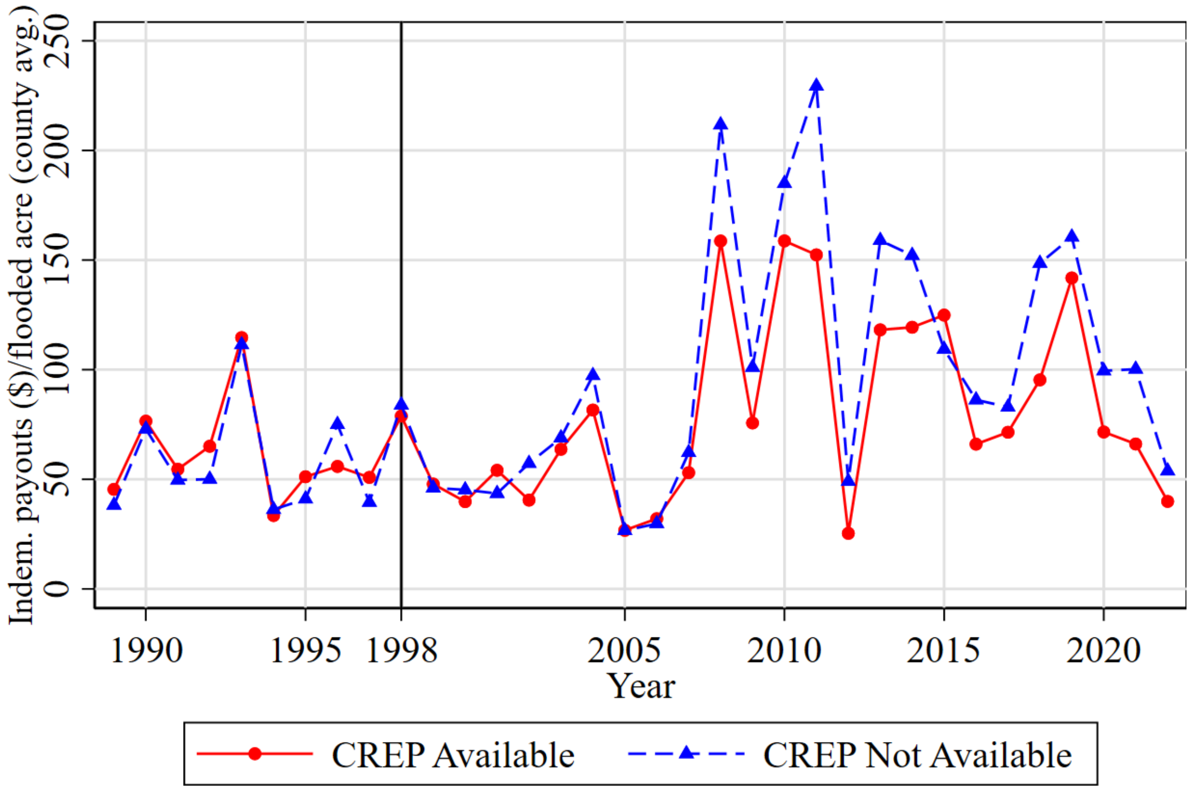
One important caveat of measuring crop loss using federal crop insurance program data is that the recorded crop loss only captures a partial view of the actual crop loss. For example, no indemnified crop acres in each year may indicate at least three possible scenarios: (i) the county did not experience any crop loss, (ii) the county had no insured crop acres regardless of the actual crop loss, or (iii) the county experienced crop loss on insured acres, but the loss was not substantial enough to trigger any indemnity payouts. These limitations have implications when estimating the flood mitigation benefits of CREP. For instance, reductions in indemnity payouts in CREP-available counties may be attributed to lower adoption rates of crop insurance compared to comparison counties, overstating the program's benefits.

To address 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 crops during the pre-policy period. For counties where CREP was introduced between 1998 and 2011, the pre-policy period spans from 1989 to the year of program introduction in each county. For counties without CREP, I include counties with insured crop acres between 1989 and 2011, which is the last year of CREP introduction in the analysis. Among 709 counties within the two farm resources regions of interest, 400 counties had insured crop acreage throughout the entire pre-policy period. In the sensitivity analysis, I conduct a robustness check expanding the analysis to 635 counties that reported any flood insurance claims on cropland during the pre-policy period. In addition, I investigate whether the crop insurance decisions between CREP-available counties and the comparison group are similar during the pre- and post-policy periods.

I find divergence in the trends of flood damage on cropland between counties with and without CREP availability after the first program introduction in the analysis region in 1998 (Figure 4). This observed divergence, however, may not necessarily be attributed to the introduction of CREP in the presence of unobserved heterogeneity and time-varying confounding factors, such as potential divergence in weather conditions and crop insurance adoption. Flooded crop losses are large in the years of major flood events in the Mississippi River Basin such as the years of 2008, 2011, 2014, and 2019. On the other hand, flooded crop losses are small in the year of severe drought such as 2012. Overall, flooded crop loss covered under the federal crop insurance program has increased due to weather anomalies combined with increasing crop insurance adoption (e.g., coverage level). Flood damage on cropland also varies spatially depending on geographical conditions, hydrological networks, and weather conditions. Figure A1 in Appendix A presents a map that shows spatial heterogeneity of flood damage on cropland across counties before CREP became available in the region of analysis in 1998.

4.3 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 counties with CREP and the comparison group share similar climate conditions, I



CREP Available: Mean = 75, SD = 113, Min = 0, Max = 953, N = 8500
CREP Not Available: Mean = 88, SD = 127, Min = 0, Max = 1112, N = 5100

Figure 4. Trends in Flooded Crop Loss in the Federal Crop Insurance Program, 1998-2022: Counties with versus without Conservation Reserve Enhancement Program

Notes: The graph shows trends in the average indemnity payouts (in 2022$) per flooded crop acre at the county level (y-axis), comparing counties with and without Conservation Reserve Enhancement Program (CREP) during years 1989-2022 (x-axis). *Source*: USDA Risk Management Agency and Farm Service Agency.

include four auxiliary weather covariates in the estimation of program effect: precipitation (mm) and growing degree days during both the post-harvest (October to March) and growing seasons (April to September) from fiscal years 1989 to 1997. These weather variables are derived from daily temperature data at a 2.5 by 2.5-mile grid-cell level, sourced from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) Climate Group (Schlenker & Roberts, 2009). Growing degree days, which represent the accumulated temperature between 10 and 29 degrees Celsius, offer a more precise measure for explaining variation in crop yield compared to average temperature alone (Auffhammer & Schlenker, 2014; Carleton & Hsiang, 2016).

5. EMPIRICAL FRAMEWORK

I provide an overview of the empirical methodology employed to estimate the causal impact of CREP introduction on crop loss due to flooding. The estimand of interest is the average treatment effect on the treated (ATT), which measures the average impact of CREP *introduction* on flood damage on cropland in counties with CREP. To estimate the ATT, I exploit the staggered rollout of CREP across counties and implement a weighted DID approach. In the following subsections, I first introduce the notation and define the estimand of interest. Then, I discuss the identification strategy and the validity of identification assumptions. Finally, I describe a partially pooled SCM by Ben-Michael et al. (2022) used to construct the comparison group in the DID setting.

5.1 Estimands of Interest

Suppose that I observe an annual crop loss for $i = 1, \dots, N$ counties over $t = 1, \dots, T$ years with variation in the timing of program introduction across counties ($N = 400$ and $T = 34$). Let T_i denote the first program-available year in a county i (i.e., the first year of the county being "treated"), assuming $T_1 \leq T_2 \leq \cdots \leq T_N$ without loss of generality. Let $j = 1, \dots, J$ denote the treated counties where CREP was eventually available by year T ($J = 250$). Let N_0 denote the number of counties where CREP was not available during the analysis period ($N_0 = 150$) 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 CREP first becomes available in county i in year $s = 1, \dots, T, \infty$. 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 mitigating benefits of CREP would generally increase with the duration of program availability (event time) for two reasons: (i) the gradual rise in program participation to establish conservation practices and (ii) the improved effectiveness of established conservation practices as vegetation on riparian buffers and wetlands matures. Let event time $k \leq K$ denote the year relative to the first year of program availability T_j ($k = t - T_j$). Then, the evolution of crop loss experience in county j treated in year T_j across event time k, relative to its average crop loss during L_j ($L_j \leq T_j - 1$) pre-policy periods (i.e., the trajectory of treated outcome) is:

$$\dot{Y}_{jT_j+k}(T_j) \equiv Y_{jT_j+k}(T_j) - \frac{1}{L_j}\sum_{l=1}^{L_j} Y_{jT_j-l}\,. \tag{7}$$

Then, for the same county, the evolution of counterfactual crop loss from its pre-policy average to event time k (i.e., time $T_j + k$) is $\dot{Y}_{jT_j+k}(\infty)$, which is equivalent to the counterfactual trajectory of post-policy crop loss had the program not been 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 the divergence in the two trajectories of crop loss:

$$\tau_{jk} = \dot{Y}_{jT_j+k}(T_j) - \dot{Y}_{jT_j+k}(\infty), \tag{8}$$

where $\tau_{jk} = 0$ for any $k < 0$ in the absence of program anticipation and spillover effects. I can aggregate the county-specific program effect across the event time to estimate the dynamic program effects. The average effect of CREP availability on counties with CREP, $k \geq 0$ years after the program onset (ATT_k) is:

$$ATT_k \equiv \frac{1}{J}\sum_{j=1}^{J} \tau_{jk} = \frac{1}{J}\sum_{j=1}^{J}\left[\dot{Y}_{jT_j+k}(T_j) - \dot{Y}_{jT_j+k}(\infty)\right]. \tag{9}$$

Finally, the estimand of interest is the overall effect of CREP introduction on crop loss across event time from 0 to K:

$$ATT \equiv \frac{1}{K+1}\sum_{k=0}^{K}\frac{1}{J}\sum_{j=1}^{J} \tau_{jk}\,. \tag{10}$$

5.2 Identification Strategy

In an ideal experiment for assessing the loss mitigating benefits of CREP using a DID approach, we would compare the trends in flooded crop losses between two counties that are identical in all aspects, except for the introduction of CREP at a certain point in time. Prior to the introduction of CREP, both counties would have had the same trajectories of crop loss due to the shared determinants of crop loss, such as inherent flood risk and trends in weather conditions ($\tau_{jk} = 0$, $k < 0$). However, after the introduction of CREP in one county, any divergence in flooded crop loss between the two counties ($\tau_{jk} \neq 0$, $k \geq 0$) would be attributed to the program's effect, providing insights into the dynamic impact of CREP availability on crop loss. In this experiment, the other county without CREP serves as a credible comparison unit, representing what the county with CREP would have experienced in the absence of the program. Thus, by examining the differential changes in flooded crop losses over time, we can estimate the loss mitigating benefits attributable to CREP.

However, my identification strategy faces two main empirical challenges. First, the spatial and temporal variation in the availability of PES programs may be driven by factors that also affect 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 introduction of PES programs to address water quality concerns. Second, the timing variation in the introduction of the program and potentially heterogeneous program effects across counties require careful selection of a comparison group to avoid bias in estimating the program effect. For instance, the program effect estimated by the conventional two-way fixed effects DID estimator would be biased in this setting (Borusyak et al., 2021; Goodman-Bacon, 2021; Baker et al., 2022; Roth et al., 2023).

My identifying variation comes from the staggered introduction of CREP across counties. I consider two alternatives for implementing DID: (i) a weighted average of DID estimates obtained by the cohort of program adoption (de Chaisemartin & d'Haultfoeuille, 2020; Callaway & Sant'Anna, 2021; Sun & Abraham, 2021), and (ii) an average of county-specific DID estimates, exploiting the county-specific variation in the year of program availability (Arkhangelsky et al., 2021; Ben-Michael et al., 2022). I implement the latter approach and establish a comparison group for each county with CREP availability using SCM (Abadie & Gardeazabal, 2003; Abadie et al., 2010, 2015). Given the catastrophic and localized nature of flood events, it is likely that each county has a specific pre-policy trend in flood damage. The latter approach is robust to such county-specific pre-trends in flood damage. Nonetheless, I also present the program effects estimated by the staggered DID estimator proposed by Callaway and Sant'Anna (2021) to examine the robustness of the findings.

To estimate the county-specific program effect across event time, τ_{jk}, I estimate the trajectory of crop loss that each county with CREP would have experienced in the absence of the program, $\dot{Y}_{jT_j+k}(\infty)$. A suitable comparison unit may not necessarily be a single county or all counties without CREP. Instead, I construct a synthetic control, which is a weighted combination of untreated counties with similar *trends* in crop loss during the pre-policy periods. SCM has been widely used in the existing literature to estimate the causal impact of policy implementation on a single unit (Abadie & Gardeazabal, 2003; Abadie et al., 2010, 2015) and on multiple units (Acemoglu et al., 2016; Kreif et al., 2016; Robbins et al., 2017; Sears et al., 2023).

The estimated average program effect across event time, $\widehat{ATT}_k$ is obtained by taking the simple average of the estimated county-specific program effect $\hat{\tau}_{jk}$ (equation (9)). This program effect estimator takes the form of a weighted DID estimator, where the weights for untreated counties are 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 include the absence of time-varying confounding factors, policy anticipation effects, and spillover effects. This estimator also addresses bias arising from potential program effect heterogeneity and timing variation in program introduction.

Time-varying confounding factors pose a threat to identification because the divergence in post-policy crop loss between counties with CREP and those without CREP could be attributed to factors other than the introduction of CREP. For instance, a decrease in crop insurance adoption in CREP-available counties after the program introduction could decrease overall reported crop losses, thus overstating the program's effect. Similarly, a decrease in excessive precipitation in CREP-available counties during the post-policy period could also overstate the program's effect. On the other hand, a decrease in the participation of other conservation programs that support similar conservation practices in CREP-available counties may underestimate the impact of CREP on crop loss. Although the assumption of no time-varying confounding factors is fundamentally untestable due to unobserved confounding factors that vary over time, I examine whether these observed time-varying confounding factors exhibit parallel trends before and after the policy to enhance the credibility of the estimated program effect.

CREP in the Mississippi River Basin mitigates concerns related to reverse causality because the program's initiation is not likely driven by an individual county's trend in indemnity receipts for crop loss. The program aims to address environmental concerns that extend beyond the immediate areas of implementation, such as the reduction of agricultural nonpoint source water pollution in the Gulf of Mexico and declining of wildlife habitats (see Allen (2005) and section 2.3 for details). In addition, the staggered rollout of CREP across counties within the same state allows for a comparison group that consists of counties without CREP in the same state or farm resource region. These counties likely have similar confounding factors such as crop type, farming practice, production and climate conditions, and regional land use policies.

The assumption of no policy anticipation effect is plausible because individual landowners may not be aware of future program availability. The availability of CREP in each county is primarily driven by the state and federal governments to address environmental quality concerns that extend across vast distances. Thus, individual landowners may not be aware of future program availability. 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.[7] Finally, CREP has strict program eligibility criteria for cropland location, cropping history, and land characteristics, which exclude cropland with high risk of loss. Overall, farmers have little incentive to manipulate crop loss in anticipation of program introduction.

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 the remaining cropland in the same farm. Spillover effects between counties, however, can bias the estimated program impact (a) downward if flood mitigating practices in upstream counties with CREP also reduce flood damage in downstream non-CREP counties that construct synthetic controls, or (b) upward if flood mitigating practices in upstream counties with CREP further reduce flood damage in downstream counties with CREP. However, unless the composition of a neighboring upstream county and the magnitude of spillover effects among neighboring counties are systematically associated with CREP availability, the estimated average program effect on flooded crop loss would not be significantly biased by spillover effects. In Section 7, I investigate whether the flood mitigation benefits vary with the number of neighboring counties with CREP.

5.3 Synthetic Control Method

To construct a comparison unit for each treated county, I employ the partially pooled SCM proposed by Ben-Michael et al. (2022) and construct a synthetic control for each treated county (Doudchenko & Imbens, 2016; Ferman & Pinto, 2021). To be specific, the partially pooled SCM allocates weights across untreated counties (including those not-yet treated[8]) to minimize the

[7] 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).

[8] For example, when estimating the initial 11 years of program effects for counties treated in 1998, not-yet treated counties include counties that were treated after 2008.

weighted average of two imbalance measures: (i) the average of difference in pre-policy trends in outcomes between the individual 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), where both fits are measured by root mean squared difference (see Appendix B for detailed weight allocation procedure).

Let $\hat{\gamma}_{ij} \geq 0$ denote the allocated weight on county i used to construct the synthetic control for treated county j, where the weights are non-uniform, sparse, and sum to 1, $\sum_i \hat{\gamma}_{ij} = 1$. Then, for each treated county j, the county-specific DID estimate, $\hat{\tau}_{jk}$, across event time k is:

$$\hat{\tau}_{jk} = \dot{Y}_{jT_j+k}(T_j) - \hat{\dot{Y}}_{jT_j+k}(\infty) \tag{11}$$

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

The estimated county-by-event time program effect $\hat{\tau}_{jk}$ can be aggregated to obtain the estimated average program effect across event time $\widehat{ATT}_k$ and the overall program effect $\widehat{ATT}$ using equations (9) and (10). For statistical inference, I use wild bootstrap to construct confidence intervals for the estimated ATT.[9]

In addition to pre-policy trends in flooded crop loss, I include average weather conditions during 1989-1997 as auxiliary covariates in choosing synthetic control weights. Historical weather conditions may capture additional information that explains future crop loss that cannot be fully explained by pre-policy trends in crop loss. For example, crop type, crop profitability, and farming practices are likely to be similar across counties that have similar weather conditions in addition to similar experience in crop loss. Thus, synthetic control counties likely consist of qualitatively similar farms compared to the treated counties, except for the availability of CREP. As a robustness check, I also present the estimation result excluding auxiliary covariates in Section 6.4.

6. RESULTS

I first show that synthetic controls for counties with CREP tend to consist of counties without CREP in the same state or neighboring states. Then, I present estimated flood mitigation benefits of CREP during the initial 11 years of program implementation, $\widehat{ATT}_k$ and $\widehat{ATT}$ in equations (9)

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

and (10). I also compare pre- and post-policy trends in potential confounding factors and placebo outcome between counties with CREP and synthetic controls. Then, I conduct sensitivity analysis to discuss the robustness of the findings, including the estimation of program effect using other DID estimator. Next, I decompose the estimated overall flood mitigation benefits into two primary mechanisms discussed in the theoretical framework by combining the theoretical model with the estimated program effects, program data, and remotely sensed land cover data. Finally, I explore spatial and temporal heterogeneity of the flood mitigation benefits of CREP.

6.1 Flood Mitigation Benefits of CREP Introduction

I find that the constructed synthetic control counties consist of untreated counties that are geographically closer to the counties with CREP (Figure 5). For example, in Iowa, 35 counties with CREP have a total of 35 synthetic controls that primarily consist of untreated counties within the same state (63 percent) and a neighboring state, South Dakota (21 percent), on average. Each synthetic control county typically consists of 5 to 11 different untreated counties with an average of 7.7 counties. Overall, the diagonal pattern in Figure 5 (excluding Tennessee and Mississippi that do not have counties with CREP) suggests that the post-policy average crop loss that counties with CREP would have experienced in the absence of the program is estimated based on the post-policy average crop loss in neighboring untreated counties that exhibit similar pre-policy trends in crop loss and production conditions.

Before the introduction of CREP, both counties with CREP and the synthetic control exhibited parallel trends in average crop loss with a small difference in level (Figure 6). After the introduction of CREP, however, the two groups experienced a divergence in flooded crop loss. The average annual indemnity payouts per flooded crop acre in counties with CREP are only \$1.6/acre lower than that in the synthetic controls during the pre-policy periods, but the gap increases to \$28.8/acre during the post-policy periods.

I find economically and statistically significant flood mitigation benefits of conservation investments made through CREP (Figure 7). In the initial 11 years of CREP implementation, the estimated average reduction in annual indemnity payouts per acre loss is \$27.3/acre, which corresponds to a 26 percent decrease from the estimated counterfactual crop loss of \$106.4/acre, that is, the average post-policy outcome in synthetic control (\$108/acre) adjusted by the pre-policy difference in average outcome (-\$1.6/acre). The flood mitigation benefits generally increase with

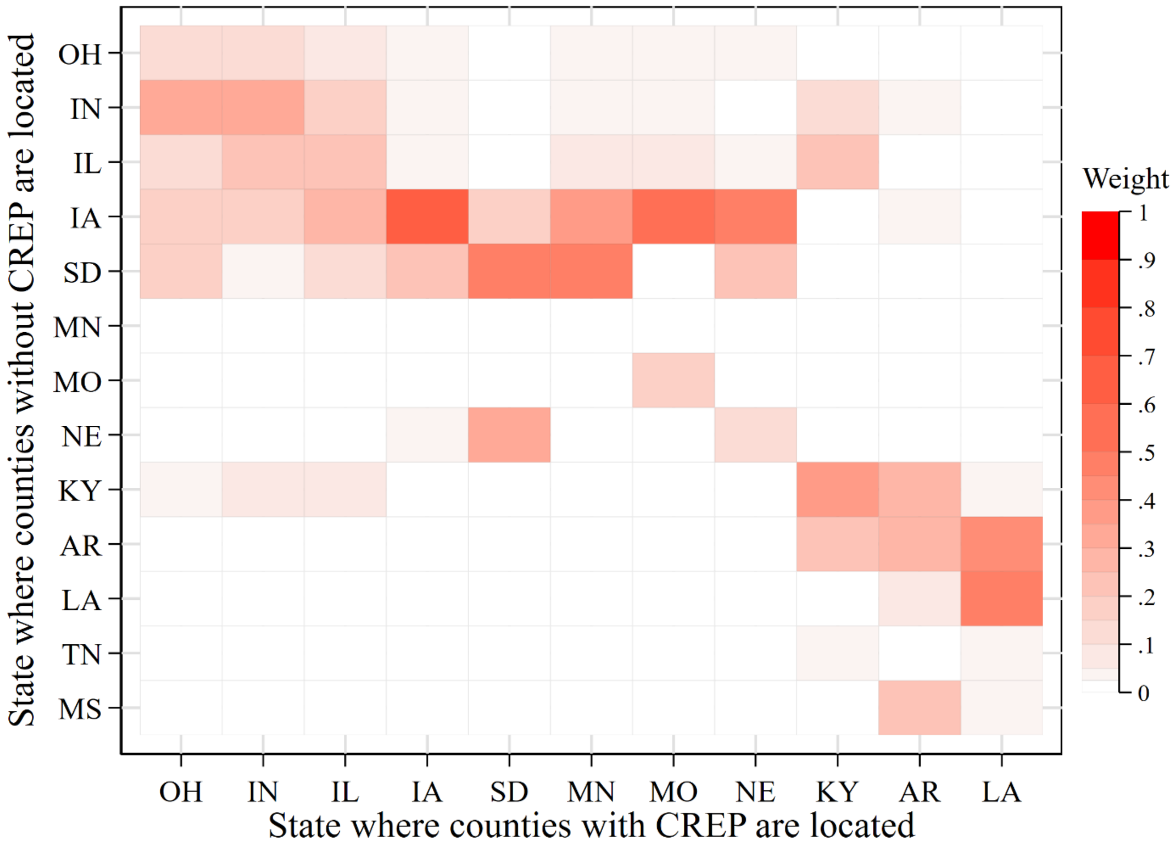
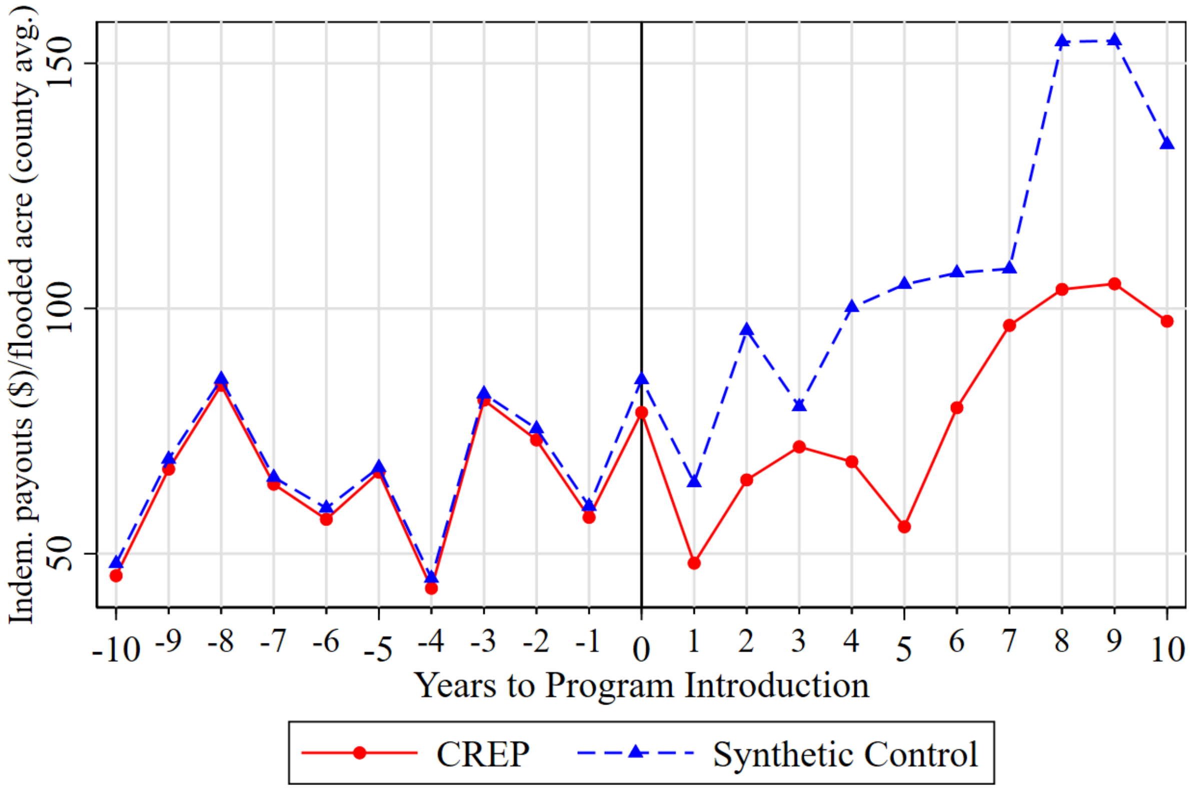


Figure 5. Spatial Distribution of Synthetic Control Weights Allocated to Untreated Counties

Notes: The figure presents the distribution of weights assigned to counties without CREP in each state (y-axis) when constructing synthetic controls for counties with CREP in a given state (x-axis). 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 state a, denoted as N_a^{trt}. Let W_{ab} denote the sum of synthetic control weights allocated to untreated counties in state b for constructing synthetic controls of treated counties in state a. The heatmap presents the ratio of W_{ab} to N_a^{trt} for each combination of state a with treated counties (x-axis) and state b with untreated counties (y-axis).

the duration of program availability. On average, the magnitude of reduction in indemnity payouts per flooded crop acre rises from $17/acre during the first 5 years to $35.8/acre after 6 to 11 years of program implementation (20 to 29 percent reduction relative to the estimated counterfactuals of $83.5/acre and $125.5/acre).

Compared to the same set of synthetic control counties, I also find that both total indemnity payouts and crop acres lost due to flooding (both numerator and denominator of the ratio outcome) in counties with CREP decreased after the introduction of CREP. During the pre-policy periods, the average annual indemnity payouts for flooded crop damage in counties with CREP are only $5,546 lower than that of synthetic control counties ($67,344 and $72,890; Figure A2 in Appendix



Pre-outcome Avg.: CREP 62.3, Synthetic Control 63.9, Pre-Diff. = -1.6
Post-outcome Avg.: CREP 79.2, Synthetic Control 108, Post-Diff = -28.8

Figure 6. Trends in Flooded Crop Loss: Counties with CREP and Synthetic Controls

Notes: The graph shows trends in average flooded crop loss (indemnity payouts per flooded acre in 2022$/acre) (y-axis) in 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls by the number of years to the program introduction (event time) (x-axis).

A). The difference, however, increases to $107,587 during the post-policy periods ($90,406 and $197,993). Similarly, the average annual flooded crop acres in counties with CREP are only 14 acres fewer than those of the synthetic control counties during the pre-policy periods (399 and 413 acres; Figure A3), while the difference increases to 244 acres during the post-policy periods (360 and 604 acres). I calculate that the introduction of CREP led to an average reduction of 53 percent in total indemnity payouts and a 39 percent decrease in crop acres lost due to flooding, compared to the synthetic control's post-policy outcome adjusted by the pre-policy difference in outcome (589 acres and $192,447 of indemnity payouts).

To assess the overall reduction in flooded crop loss due to the introduction of CREP, I combine (a) the reduced indemnity payouts per flooded crop acres with (b) the avoided indemnity payouts resulting from the reduced number of flooded crop acres in counties with CREP. First, CREP

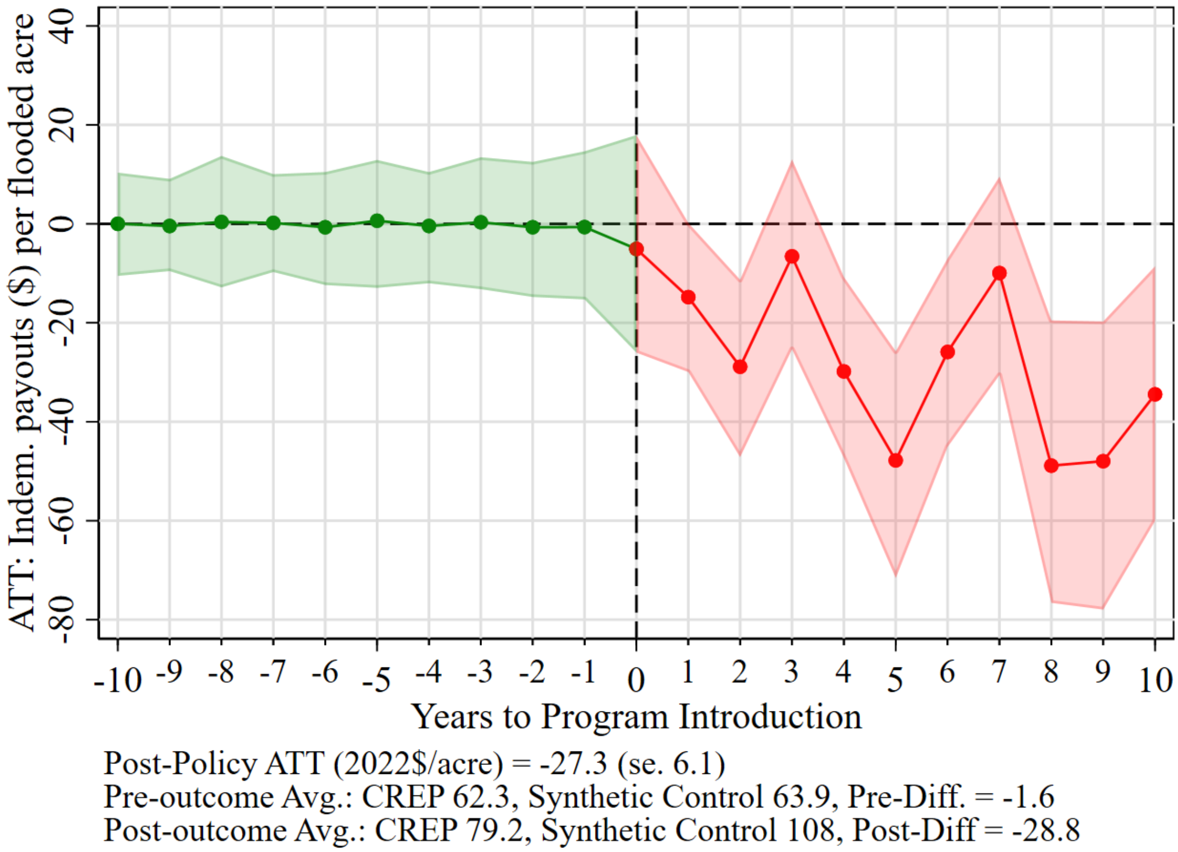


Figure 7. Estimated Impact of CREP Introduction on Flooded Crop Loss

Notes: The graph shows the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss (indemnity payouts per flooded crop acre in 2022$/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 250 counties with CREP and their synthetic controls. In addition to lagged outcomes, total 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 untreated and not-yet treated counties to construct synthetic controls. Confidence intervals (95%) are constructed using wild bootstrap.

reduced the extent of damage on 359.9 flooded crop acres by $27.3/acre during the post-policy period. Second, the reduced number of flooded crop acres is 229.6 acres (Figure A3) and the avoided indemnity payouts on those flooded acres are $106.4/acre (Figure 6). This calculation yields a total savings of $94 million in indemnity payouts that would have been paid to the insureds in the absence of CREP in 250 counties during the initial 11 years of program implementation.

To obtain the total avoided flood damage in terms of crop acreage, I take the ratio of $94 million in indemnity payouts to the estimated counterfactual post-policy average indemnity payouts in counties with CREP ($106.4/acre), which yields roughly 900,000 acres. Furthermore, combining the reduction in total indemnity payouts ($94 million) with the government's program spending during the same period ($622 million), the financial spillover effects of introducing CREP to the federal crop insurance program equal a $151 reduction in insurance claims for flooding per $1,000 of CREP spending. Given that the indemnity payout only covers a portion of flood damage, I use the post-policy average of insurance coverage level in counties with CREP (73 percent) and calculate that the flood mitigation benefits of CREP introduction are $207 (=$151/0.73) per $1,000 of CREP spending.

The magnitude of estimated flood mitigation benefits in agriculture compared to program payments (21 percent) could serve as a lower bound estimate if either (i) the natural infrastructure established through CREP remains effective beyond the initial contract period or (ii) the flood mitigation benefits extend beyond flood damage on cropland. For instance, conservation covers established through CRP, such as grass, tree, and wetlands, tend to endure even after the contract expires (Bigelow et al., 2020). In addition, Kousky and Walls (2014) find that floodplain conservation in Missouri would reduce flood damage on residential property, yielding a benefit-cost ratio of 0.45. On the other hand, the estimated magnitude of benefits relative to the program costs could be overstated because the program expenditure only includes annual payment and excludes other types of program costs, such as payments to share the cost of establishing conservation practice and administrative expenses.

The magnitude of flood mitigation benefits relative to program costs is noteworthy when compared to other social benefits of PES programs. On a national scale, the environmental benefits of CRP account for 70 to 85 percent of the program payments (0.70-0.85) although the benefit-cost ratio varies across regions (Hansen, 2007). Focusing on the Indian Creek watershed in Iowa, CRP's environmental benefits could potentially outweigh program payments by a factor ranging from 1.5 to 8.1 (Johnson et al., 2016). The environmental benefits in these studies include improvements in soil, air, and water quality, wildlife habitats, and flood mitigation in residential areas. Other relevant studies find a benefit-cost ratio of 0.012 for groundwater benefits of CREP in Kansas that retires irrigation water rights (Manning et al., 2020), and a benefit-cost ratio of 2.31 for the crop yield benefits of wetland easement programs in the United States (Karwowski, 2022).

6.2 Confounding Factors

The 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, or (iii) conservation investments from other similar PES programs. Although the assumption of no time-varying confounding factor is fundamentally untestable due to unobserved confounding factors, I provide supportive evidence of the assumption by investigating whether important time-varying confounding factors have relatively parallel pre- and post-policy trends.

First, I find that both the number of insured acres and the coverage level adopted have relatively parallel pre- and post-trend between counties with CREP and synthetic control group (Figures A4 and A5). The availability of CREP and adoption of conservation practices may not significantly affect insurance adoption for two reasons: (i) the loss mitigating benefits of conservation practices may be uncertain to landowners, at least in the short run, and (ii) the federal crop insurance program covers loss in yield and revenue caused by multiple perils even including a decline in crop price while conservation practices may not.

Second, the post-policy divergence in crop losses between counties with CREP and the 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 the crop growing season, April to September, exhibit relatively parallel pre- and post-policy trends (Figures A6 and A7). Thus, the post-policy reduction of crop loss in counties with CREP may not be driven by differential climate conditions.

Lastly, I examine trends in enrolled acres under two PES programs that share similar conservation objectives with CREP: (i) CRP (excluding CREP), which offers payments to landowners for taking environmentally sensitive cropland out of production for 10-15 years, and (ii) Wetland Reserve Easement component of the Agricultural Conservation Easement Program (previously Wetland Reserve Program), which conserves wetlands for 30 years under easement contracts. I do not find significant divergence in post-policy trends of conservation investments made by these programs between counties with CREP and the synthetic control (Figures A8 and A9). Thus, the post-policy reduction of flood damage in counties with CREP may not be driven by differential conservation investments made by other similar programs.

6.3 Placebo Test

I investigate whether a placebo outcome that should not be affected by conservation investments through CREP diverges after the introduction of CREP between counties with CREP and the synthetic control. The federal crop insurance program's revenue protection covers the insured's revenue loss due to a decline in crop price in the futures market (see Section 2.4 for details). Indemnity payouts resulting from a decrease in crop price, therefore, serve as a placebo outcome that should remain unaffected by the availability of CREP. Contrary to the post-policy divergence observed in indemnity payouts due to flooding between the two groups, I do not find post-policy divergence in payouts related to low crop price (Figure A10). This finding suggests that the comparison between counties with CREP and the synthetic control is expected to reveal differences in outcomes that are specifically related to the availability of CREP, such as the reduction in flood damage on cropland induced by the establishment of natural infrastructure. In addition, this finding implies that the observed divergence in flood insurance claims between the two groups is unlikely to be driven by differences in loss reporting behavior or transaction costs associated with receiving insurance payouts between farmers in these groups.

6.4 Sensitivity Analysis

The findings are qualitatively robust to several modifications made in the estimation of program effects. First, when only pre-policy trend in flooded crop loss is considered for allocating synthetic control weights to untreated counties, the estimated reduction in flooded crop damage decreases from 26 percent to 20 percent and is statistically significant (Figure A11). In this case, synthetic controls are untreated counties that are geographically farther away from the treated counties as weather conditions are not considered in allocating weights to untreated counties. Second, flood mitigation benefits remain persistent and statistically significant even when estimating the program effects for up to 21 years of implementation, yielding a 27 percent reduction in flood damage (Figure A12). Third, the findings remain qualitatively similar when using a different functional form of the crop loss outcome. The estimated program effect, using inverse hyperbolic sine (IHS) transformation of the outcome to account for years with no flooded crop loss, shows statistically significant flood mitigation benefits with a similar trajectory of flood mitigation benefits over time (Figure A13) (Bellemare & Wichman, 2020). Finally, the findings are also qualitatively similar when using an alternative crop loss measure, that is, the ratio of total indemnity payouts to total liability (i.e., loss cost) (Figure A14).

The findings are also not driven by a few counties with extreme program effects and are also robust to relaxed screening criteria for counties included in the analysis. First, 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 $\hat{\tau}_{jk}$ in equation (11), which yields \$28.4/acre and \$29.8/acre reduction in indemnity payouts per flooded crop acre compared to \$27.3/acre in baseline. Similarly, excluding counties with top and bottom 1 or 5 percentile of the estimated overall program effect yields similar \$26.7/acre and \$26.9/acre reductions in indemnity payouts per flooded crop acre. Finally, the findings remain consistent when expanding the analysis to 635 counties with any flood insurance claims on cropland during the pre-policy period. The estimated program effect remains at \$23.2/acre and is statistically significant (Figure A15).

Finally, the findings remain robust when implementing DID by the cohort of program introduction (Table A2). Using the same data set, I use the staggered DID estimator proposed by Callaway and Sant'Anna (2021) with untreated and not-yet treated counties as the control group. Without the inclusion of weather covariates, I observe pre-trends in flood damage between the comparison group and counties with CREP (Figure A16). The estimated post-policy ATT is an \$8.4/acre reduction in flood damage but is not statistically significant. The presence of pre-trends in flood damage may mask the true program effects in this case. When accounting for the same set of weather covariates, the pre-trends in flood damage persist with a reduced magnitude (Figure A17). However, the magnitude of the estimated post-policy ATT increases to a \$17.9/acre reduction in flood damage and is statistically significant. Thus, both the average of county-specific DIDs with SCM (Figure 7) and the weighted average of DIDs for each cohort of program adoption (Figure A17) deliver qualitatively similar findings that the introduction of CREP has mitigated flood damage on cropland. Overall, the sensitivity analysis demonstrates the robustness of the findings.

6.5 Decomposing the Flood Mitigation Benefits: Conversion and Protection Effects

Section 3.3 outlined two primary mechanisms through which the introduction of PES program can influence flood damage on cropland: (i) the removal of at-risk cropland from production for conservation purposes (the conversion effect) and (ii) the reduced extent of damage on remaining cropland due to the established natural infrastructure (the protection effect). Although the theoretical model operates at the farm level, the relative contributions of these two channels to the overall estimated loss mitigating benefits of CREP are calculated by aligning theoretical predictions with empirical analysis at the county level.

Using equation (6) from the theoretical framework, I rearrange terms to derive the following expression:

$$\underbrace{\beta^* q D_e(L - e^*)}_{\text{protection effect}} \approx \underbrace{\frac{\beta^* \Delta q D(e^*)(L - e^*)}{\Delta e}}_{\text{reduced insurance claims per acre}} - \underbrace{\beta^* q D(e^*)}_{\text{conversion effect}} . \qquad (12)$$

The relative contribution of the protection effect on the LHS of equation (12) can be approximated by (a) the total reduction in flood insurance claims per acre enrolled in the program less (b) the conversion effect, which represents the avoided flood insurance claims per acre of cropland removed from production and enrolled in CREP. I calculate these two components by estimating the terms on the RHS of equation (12).

Consider the first ratio term on the RHS of equation (12). To calculate the total reduction in flood insurance claims (the numerator), I use the estimated reduction in flood insurance claims in counties with CREP during the initial 11 years of the program's implementation (post-policy period), which amounts to \$94 million (Section 6.1). The change in conservation acreage induced by CREP (the denominator) equals the total crop acres enrolled in the program during the post-policy period, which is 380,000 acres. Dividing the total reduction in insurance claims by the conservation acreage yields a \$247 reduction in flood insurance claims per acre enrolled in CREP during the post-policy period, or an equivalent \$22.5 reduction in annual indemnity payouts per acre enrolled in CREP (\$247/11 years).

Next, consider the conversion effect, which represents the avoided flood insurance claims per crop acre enrolled in the program due to the removal of cropland. The expected annual flood insurance claims that would have been made by crop acres enrolled in CREP is approximated by the average flood insurance claims in control group during the post-policy period, after adjusting for the pre-policy difference, which yields \$192,447 (Figure A2). Assuming these claims are made by crop acres located within floodplains,[10] I calculate the number of crop acres within floodplains by overlaying (i) a map of areas with a 1 percent annual chance of flooding (the 100-year

[10] Using the total crop acres in the county as the denominator would understate the avoided flooded crop loss for cropland enrolled in CREP because the program explicitly targets cropland adjacent to water bodies.

floodplain or Special Flood Hazard Area) obtained from Woznicky et al. (2019) and (ii) maps of cropland from 1989 to 2021 obtained from the United States Geological Survey (USGS)'s Land Change Monitoring, Assessment, and Projection (LCMAP).[11] The post-policy average crop acres within floodplains in synthetic control counties (34,047 acres) less the pre-policy difference between CREP and control counties (10,006 acres) yields 24,041 acres that approximates the counterfactual cropland within floodplains in counties with CREP during the post-policy period. Taking the ratio of the two yields that the avoided annual flood insurance claims for cropland enrolled in CREP equal \$8/acre (\$192,447/24,041 acres).

Finally, combining the two terms on the RHS of equation (12) reveals that the conversion effect amounts to \$8 out of the total \$22.5 reduction in annual indemnity payouts per acre enrolled in CREP. This implies that the conversion effect accounts for approximately 35 percent of the estimated flood mitigation benefits of CREP, while the remaining 65 percent is attributed to the protection effect during the initial 11 years of program implementation.

7. PROGRAM EFFECT HETEROGENEITY

The impact of PES programs on mitigating crop losses can vary spatially and temporally as shown in equation (6) in Section 3.3. To explore the program effect heterogeneity, I conduct a descriptive analysis to examine the linear relationship between the estimated county-level program effects across event time and county characteristics, including potentially endogenous factors such as the extent of program participation and crop insurance adoption. To be specific, I regress the estimated county-by-event time program effects on flooded crop loss, $\hat{\tau}_{jk} (0 \leq k \leq 10)$ in equation (11), on county-level characteristics that could explain the differences in loss mitigating benefits. These characteristics include whether a county is located downstream of the Mississippi River Basin, the adoption of alternative flood control measures such as levees, the adoption of crop insurance, the overall resilience of the county to natural disasters, weather conditions, and the acreage enrolled in CREP. Table 2 provides a full list of county characteristics with summary statistics. In this analysis, I use 2,666 out of 2,750 estimated county-by-event time program effects from 250

[11] See Woznicky et al. (2019) for the detailed discussion on the model used to generate the floodplain map. The data and descriptions are available at: https://www.epa.gov/enviroatlas/forms/enviroatlas-data-download. The data and descriptions about the Primary Land Cover in LCMAP Conterminous United States (CONUS) Collection 1.3 are available at: https://www.usgs.gov/special-topics/lcmap/lcmap-data-access.

Table 2. Descriptive Statistics: Heterogeneity Analysis

Variable Description	Mean	SD
Estimated Program Effect, county-by-post event time $\left(\hat{\tau}_{jk}, 0 \leq k \leq 10\right)$		
ATT: Indemnity payouts per flooded crop acre ($/acre in 2022$)	-28.5	123.1
Conservation Reserve Enhancement Program (CREP)		
Duration of CREP availability in years	4.9	3.1
Acreage enrolled	1158.2	2335.3
Inter-County Spillover Effects		
Number of neighboring counties with CREP	4.7	1.6
Upstream v. Downstream		
= 1 if a county is located in the Mississippi River Portal region (downstream of Heartland region)	0.05	0.23
Alternative Flood Mitigation Measure		
Area protected by levees (acre, 1,000s)	18.2	80.4
Federal Crop Insurance Program Participation		
Coverage level insured (%, area-weighted)	73.0	6.1
Crop acres insured (1,000s)	184.8	91.3
Community Resilience to Natural Hazard		
FEMA Community Risk Factor	1.1	0.1
Weather (crop growing season)		
Total precipitation (mm)	623.6	152.9
Total growing degree days (10-29 Celsius)	1722.5	292.9
Number of observation (CREP county-by-post policy event time): 2,666		

Notes: The table presents summary statistics of variables used in the analysis of program effect heterogeneity for 250 counties that introduced CREP by 2011. Out of 2750 estimated county-by-event time post-policy effects, 84 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).

counties with CREP for 11 years of post-policy period because county-level weather data are not available for the year 2020-2021. The results of the linear regression are presented in Table 3.

7.1 Nature-based Infrastructure Established through CREP

A potential mechanism of the estimated loss mitigating benefits of the PES program availability is the establishment of conservation practices subsidized by the program. I use the cumulative

Table 3. Program Effect Heterogeneity

Outcome: ATT Indemnity payouts per flooded crop acre (in 2022$)	Estimate (s.e.)
Panel A. Conservation Reserve Enhancement Program (CREP)	
Duration of CREP availability in years	-2.04* (0.96)
Number of acres enrolled, standardized	-12.6*** (3.28)
Panel B. Inter-County Spillover Effects	
Number of neighboring counties with CREP availability, standardized	1.18 (1.68)
Panel C. Upstream v. Downstream (Heartland versus Mississippi River Portal)	
= 1 if a county is located downstream of the Mississippi River	-82.4*** (22.3)
Panel D. Alternative Flood Mitigation Measure (Gray Infrastructure)	
Area protected by levees, standardized	6.24 (4.99)
Panel E. Federal Crop Insurance Program Participation	
Coverage level insured (%, area-weighted), standardized	-13.9*** (3.02)
Crop acres insured (1,000s), standardized	8.60** (2.96)
Panel F. Community Resilience to Natural Hazard	
FEMA Community Risk Factor	-1.83 (2.65)
Panel G. Weather (crop growing season)	
Total precipitation (mm) Apr-Sept, standardized	15.7*** (2.66)
Total Growing degree days (10-29 Celsius), standardized	16.2*** (3.93)
Constant	-19.6* (9.63)
Outcome Mean: ATT Indemnity payouts per flooded crop acre (in 2022$)	-28.5
Num. Observations (CREP county-by-post policy event time)	2,666
R-squared	.052
F-statistics	14.96

Notes: The table presents a linear association between the estimated loss mitigating benefits of CREP and county-level characteristics, obtained from a linear regression with multiple predictor variables. Standard errors are in parentheses and clustered at the county-level.
*** p<.01, ** p<.05, * p<.1

acreage of conservation practices established through CREP to measure the amount of natural infrastructure established due to the program introduction.

I find that the magnitude of benefits increases 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 3). This confirms that the estimated loss mitigating benefits are likely driven by the adoption of flood mitigation practices on agricultural land under CREP. The duration of program availability may also partially capture the maturity of vegetation on conservation practices installed through the program.

7.2 Inter-County Spillover Effects

I explore the extent of inter-county spillover effects by examining whether the magnitude of flood mitigation benefits vary with the number of neighboring counties with CREP availability. Conservation practices established in one county may affect flood risk of neighboring counties because they are often intricately connected through hydrological networks, with water flowing both into and out of each other. Thus, the flood mitigation benefits of conservation practices are not necessarily unidirectional from upstream to downstream counties, while the effects may diminish with distance due to watershed processes, landscape geography and topography, soil characteristics, and weather conditions (Acreman & Holden, 2013; Narayan et al., 2017; Wu et al., 2023).

I find that the extent of loss mitigating benefits varies little with the number of neighboring counties with CREP (Panel B of Table 3). This finding implies that the loss mitigating benefits of CREP introduction are primarily confined to the cropland within the county. The decomposition of flood mitigation benefits in Section 6.5 also suggests that the conversion effect accounts for 35 percent of the overall benefits, which may not contribute to spatial spillover effects. On the other hand, if spillovers affect both CREP and non-CREP counties, they may offset each other, resulting in little variation in estimated flood mitigation benefits. In both scenarios, inter-county spillover effects would not significantly bias the estimated flood mitigation benefits.

7.3 Upstream versus Downstream Farm Resource Regions

Counties in the Mississippi River Portal region, located downstream of the Mississippi River Basin, may have higher flood risk compared to counties in the Heartland region, located upstream of the Basin. I find that the loss mitigating benefits are greater in the Mississippi River Portal region where the flood risk is inherently high (Panel C of Table 3). This indicates that the implementation of PES programs could be an effective production risk management strategy in downstream areas.

7.4 Presence of Infrastructure for Flood Mitigation

Levee construction along streams and rivers 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 may have a smaller flood mitigation impact compared to areas without existing flood mitigation measures. To assess the interaction between protection services provided by green and gray infrastructures, I explore a linear association between the magnitude of estimated loss mitigating benefits of CREP and the area of floodplain excluded from floodwater by levee systems, obtained from the U.S. Army Corps of Engineer's National Levee Database.[12]

I find suggestive evidence that the loss mitigating benefits could be greater in areas with little protection from flood by levees (Panel D of Table 3). Given that the association is not statistically significant, the loss mitigating benefits of nature-based infrastructure also seem to remain robust to the existence of gray infrastructure.

7.5 Crop Insurance Adoption

The magnitude of financial spillover effects on the federal crop insurance program may vary depending on the extent of crop insurance adoption in the county as shown in Section 3. For example, counties heavily reliant on crop insurance may experience a greater decrease in crop insurance claims compared to counties with low extent of insurance adoption.

I find that the flood mitigation benefits of CREP are higher in counties with a high insurance coverage level but lower in counties with a larger insured acreage (Panel E of Table 3). This suggests that the loss mitigating benefits of PES programs could be more significant in heavily insured counties by promoting the adoption of risk-reducing practices under extreme weather events. Conversely, the adoption of crop insurance on the extensive margin, measured by the number of insured crop acres, serves as an indicator of a county's involvement in crop production (e.g., a proxy for total planted acres), rather than the extent of loss coverage against production risk, because of substantial government subsidies on crop insurance. This distinction between the number of insured acres and the coverage level potentially explains why flood mitigation benefits appear smaller in counties with a higher number of insured crop acres.

This finding indicates 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 calculations (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 (i.e.,

[12] The data and detailed descriptions can be accessed at: https://levees.sec.usace.army.mil/.

conservation cover) before the subsequent crop season. Similar premium discounts could be considered for practices that enhance streambank protection and restore wetlands.

7.6 Community Resilience to Natural Disaster

Lastly, the magnitude of loss mitigating benefits provided by natural infrastructure may vary depending on a county's inherent vulnerability to climate change impacts. The Community Risk Factor, 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.[13] The Community Risk Factor 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 index ranges from 0.5 to 2, with higher values indicating weaker resilience to natural disasters.

I find that the magnitude of loss mitigating benefits exhibits little variation with the Community Risk Factor (Panel F of Table 3). This suggests that the loss mitigating benefits of nature-based infrastructure established through PES programs remain robust for communities with high resilience to climate-related risks.

8. CONCLUSION

Global initiatives to address the impact of climate change, such as the Nature-Based Solution Roadmap at COP 27 and the World Bank Group's Climate Change Action Plan, highlight the importance of restoring natural infrastructure. Payment for ecosystem services programs play a pivotal role in these efforts by offering financial incentives to farmers and landowners to establish forests and wetlands. Existing research has shown that these conservation efforts may enhance resilience against weather anomalies associated with climate change. However, there remains a gap in understanding the cost-effectiveness of implementing PES programs to mitigate economic losses and support climate change adaptation.

This study provided theoretical and empirical analyses of how the introduction of PES programs can mitigate economic losses in agriculture under extreme weather events. The theoretical analysis showed how introducing PES program payments increases the adoption of

[13] The data and detailed descriptions can be accessed at: https://www.fema.gov/sites/default/files/documents/fema_national-risk-index_technical-documentation.pdf.

conservation practices, which subsequently reduces crop losses and insurance indemnity payouts with potential heterogeneity in the magnitude of the loss mitigating benefits of PES programs. The empirical analysis leveraged variation in the timing of CREP availability across counties and employed two weighted DID approaches to estimate the flood mitigation benefits of CREP: (i) a county-specific DID using SCM and (ii) a cohort-specific DID by the year of program introduction.

The results from both empirical approaches consistently showed that the introduction of CREP significantly mitigated flood damage to croplands. The implementation of CREP also led to a substantial reduction in insurance indemnity payouts from the federal crop insurance program, particularly in counties that rely heavily on crop insurance to manage agricultural production risks. The magnitude of these benefits varied significantly across regions and tended to increase with the duration of program availability. Overall, although CREP was primarily motivated by objectives such as addressing agricultural nonpoint source water pollution and restoring wildlife habitats, it also provides substantial climate change adaptation benefits by converting at-risk cropland into natural infrastructure that mitigates the extent of damage caused by extreme weather events.

This study has several caveats and limitations. First, the magnitude of the loss mitigating benefits from PES programs, as well as the relative contributions of the conversion and protection effects, likely vary substantially across regions and policy contexts, as suggested by the theoretical and empirical analyses. Second, while limited evidence of spatial spillover effects was observed using county-level data, this does not rule out the possibility of spillover effects among farms within a county. Third, the program payment data included only annual payments and excluded cost-share payments and administrative costs associated with establishing natural infrastructure, potentially overstating the relative magnitude of benefits to payments. However, the flood mitigation benefits are likely to persist beyond the 11 years analyzed, increasing long-term program benefits. Fourth, the flood damage data excluded losses on uninsured cropland and minor crop damages not covered by the federal crop insurance, potentially understating the broader impacts of PES programs. Finally, the empirical analysis focused on a land diversion PES program implemented in regions with intensive crop production and substantial flood risk, necessitating careful consideration of the external validity of the findings.

Despite these caveats and limitations, this study provides robust causal evidence that PES programs contribute to sustainable agriculture by mitigating crop loss and offering valuable protection against increasing extreme weather events. Furthermore, the findings suggest that PES programs can enhance the sustainability of existing agricultural risk management programs by reducing indemnity payouts triggered by weather-related risks. Thus, future benefit-cost analyses of PES programs should incorporate the loss mitigating benefits of natural infrastructure established by these programs, in addition to their environmental benefits, to provide a comprehensive evaluation of ecosystem services programs. Overall, these findings underscore the critical role of PES programs in facilitating nature-based solutions for climate change adaptation.

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APPENDIX A. SUPPLEMENTARY TABLES AND FIGURES

Table A1. Timing Variation of Conservation Reserve Enhancement Program (CREP) Availability and Participation

	Number of Counties				Fiscal Year of Program Availability/Participation	
State	Program Participation	Program Available	Program Not Available	Total	Availability (min, max)	Participation (min, max)
IL	37	40	15	55	(1998, 2011)	(1998, 2012)
MN	41	41	0	41	(1999, 2006)	(1999, 2008)
OH	30	31	9	40	(2000, 2005)	(2000, 2006)
MO	18	23	10	33	(2001, 2007)	(2002, 2008)
IA	30	35	49	84	(2002, 2002)	(2003, 2021)
AR	3	4	14	18	(2002, 2007)	(2002, 2008)
NE	13	13	5	18	(2003, 2003)	(2003, 2004)
LA	6	10	5	15	(2006, 2011)	(2006, 2006)
IN	39	41	14	55	(2006, 2011)	(2006, 2022)
KY	2	2	8	10	(2007, 2007)	(2007, 2008)
SD	10	10	9	19	(2010, 2010)	(2010, 2012)
MS	0	0	9	9	N/A	N/A
TN	0	0	3	3	N/A	N/A
Total	229	250	150	400		

Notes: The table presents the number of counties with CREP 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 A2. Estimated Impact of CREP Introduction on Flood Damage on Cropland

DID Estimator	Ben-Michael et al. (2022)		Callaway & Sant'Anna (2021)	
Weather Covariates	No	Yes	No	Yes
Years to CREP Introduction	Estimated Program Effects ATT (s.e.)			
-10	-0.5 (5.4)	0 (5.3)	-23.8 (7.1)*	-19.2 (7.2)
-9	0 (5.1)	-0.4 (4.7)	15.7 (6.4)	11.9 (7.2)
-8	0.2 (6.6)	0.4 (6.8)	18.1 (5.3)*	11.5 (7)
-7	0 (5.8)	0.2 (5)	-18.3 (5.7)*	-4.9 (6.9)
-6	-0.3 (5.4)	-0.7 (5.8)	-0.1 (6)	-3.6 (7.1)
-5	0.1 (6.8)	0.6 (6.6)	13 (6.6)	3.5 (7.6)
-4	-0.8 (5.8)	-0.4 (5.7)	-27.8 (7.3)*	-24.3 (12.1)
-3	0 (6.8)	0.3 (6.7)	14 (6.7)	21.6 (8.9)
-2	-0.3 (8.3)	-0.7 (7)	3.2 (7.1)	-5.9 (8.7)
-1	-0.5 (7.7)	-0.7 (7.6)	-16.8 (8.1)	-8.1 (10.5)
0	0.7 (9)	-5.1 (11.3)	11 (8.7)	10.4 (10.3)
1	-10.8 (7.5)	-14.8 (7.6)	-3.6 (8.2)	-4.8 (10.2)
2	-21.9 (9.4)*	-28.9 (9)*	-15.3 (7.4)	-10.2 (10.1)
3	-1.4 (9.7)	-6.6 (9.5)	-2.3 (9.6)	-2 (11.7)
4	-23.1 (9.7)*	-29.8 (9.4)*	-5.6 (8.9)	-14.3 (11.7)
5	-44.1 (10.9)*	-47.8 (12.2)*	-31.1 (9.3)*	-35.6 (11.1)*
6	-13 (10.3)	-25.9 (10)*	-3.9 (9.2)	-29.8 (12.5)
7	1.3 (11.1)	-9.9 (10.7)	1.8 (10.4)	-5.2 (10.9)
8	-28.6 (14.4)*	-48.9 (14.7)*	-15.3 (10)	-30.7 (11.6)
9	-29.4 (12.7)*	-48 (15.2)*	-17.9 (12.6)	-31.5 (13.9)
10	-18.3 (11.8)	-34.4 (13.3)*	-9.4 (10)	-43 (13.3)*
Post-Policy ATT	-17.1 (6.4)*	-27.3 (6.1)*	-8.3 (6.4)	-17.9 (7.3)*
Num. Obs. (county-by-year): counties with CREP (250-by-34); without CREP (150-by-34)				

Notes: The table presents the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss, measured by total indemnity payouts (2022$) per flooded crop acre, by event time (the number of years to the program introduction). Two DID estimators are implemented: (i) a partially pooled synthetic control method in Ben-Michael (2022) and (ii) DID with staggered program adoption in Callaway and Sant'Anna (2021). Weather covariates include precipitation (mm) and growing degree days during the post-harvest (October to March) and crop growing seasons (April to September). Symbol * indicates that the estimate is outside of the 95% confidence intervals constructed using wild bootstrap in Ben-Michael (2022) and multiplier bootstrap in Callaway and Sant'Anna (2021).

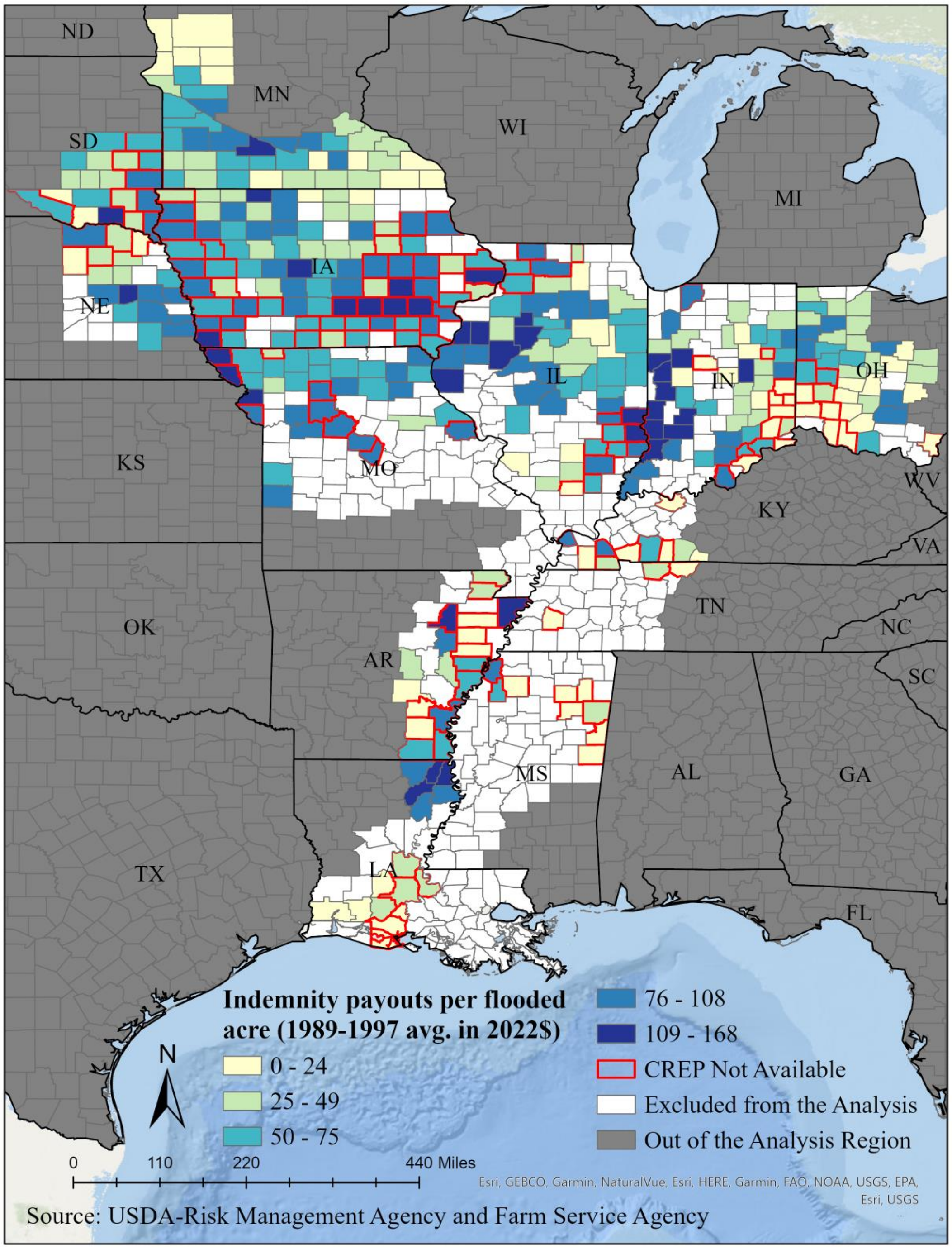


Figure A1. Spatial Heterogeneity of Flood Damage on Cropland Before 1998: Heartland and Mississippi River Portal Regions

Notes: The figure shows a map of counties in the analysis with spatial heterogeneity in flooded crop loss prior to the introduction of CREP across the entire region. Out of a total of 709 counties in the Heartland and Mississippi River Portal regions, the analysis includes (i) 250 counties that introduced CREP in years between 1998 and 2011 and had insured crop acres from 1989 to the year of CREP introduction, and (ii) 150 counties that had not introduced CREP until 2022 and had insured crop acres from 1989 to 2011.

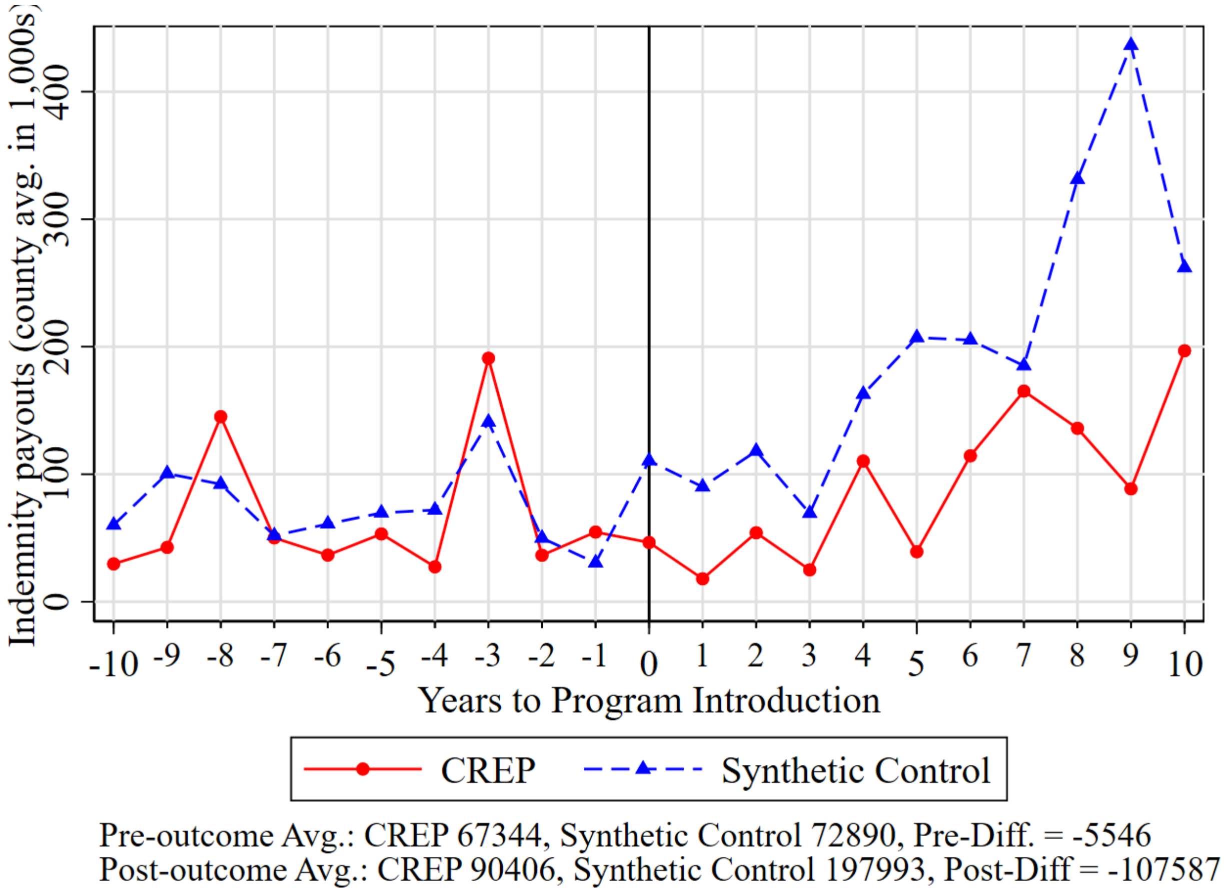
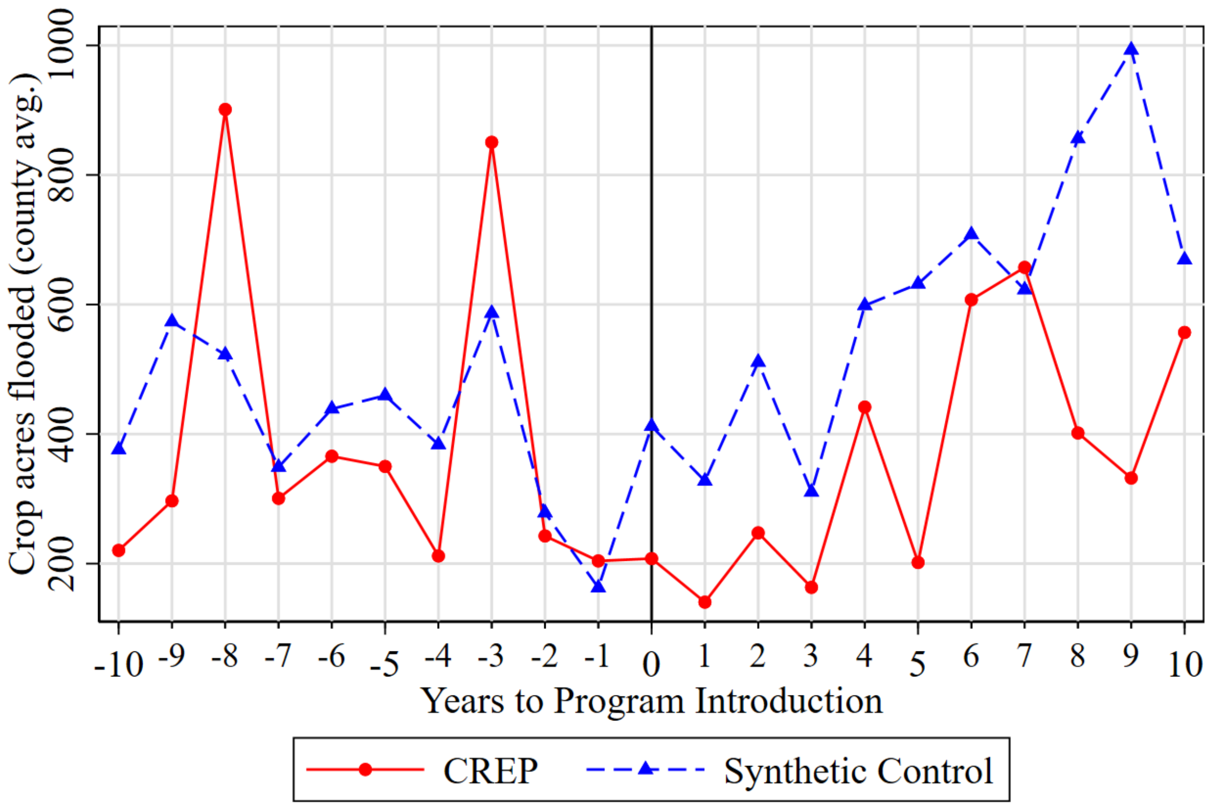


Figure A2. Trends in Indemnity Payouts due to Flooded Crop Loss: Counties with CREP and Synthetic Controls

Notes: The graph shows trends in county-level average indemnity payouts due to flood damage on cropland (in 2022$) (y-axis) by event time (x-axis) in counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of 150 counties without CREP.



Pre-outcome Avg.: CREP 399, Synthetic Control 413.2, Pre-Diff. = -14.2
Post-outcome Avg.: CREP 359.9, Synthetic Control 603.7, Post-Diff = -243.8

Figure A3. Trends in Crop Acres Flooded: Counties with CREP and Synthetic Controls

Notes: The graph shows trends in county-level average crop acres damaged due to flooding (y-axis) by event time (x-axis) in counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of 150 counties without CREP.

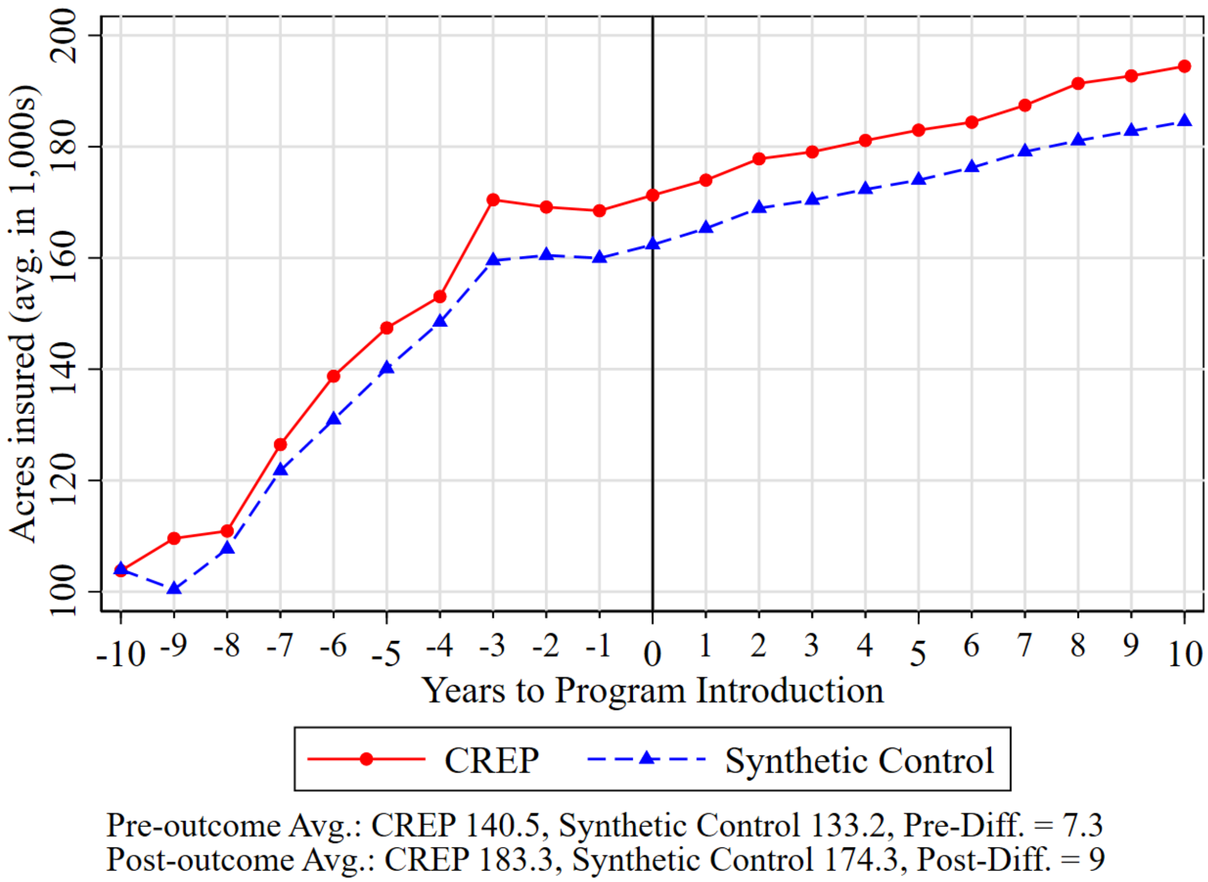


Figure A4. Trends in Acres Insured under the Federal Crop Insurance Program: Counties with CREP and Synthetic Controls

Notes: The graph shows trends in county-level average insured acres (y-axis) by event time (x-axis) in 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of 150 counties without CREP.

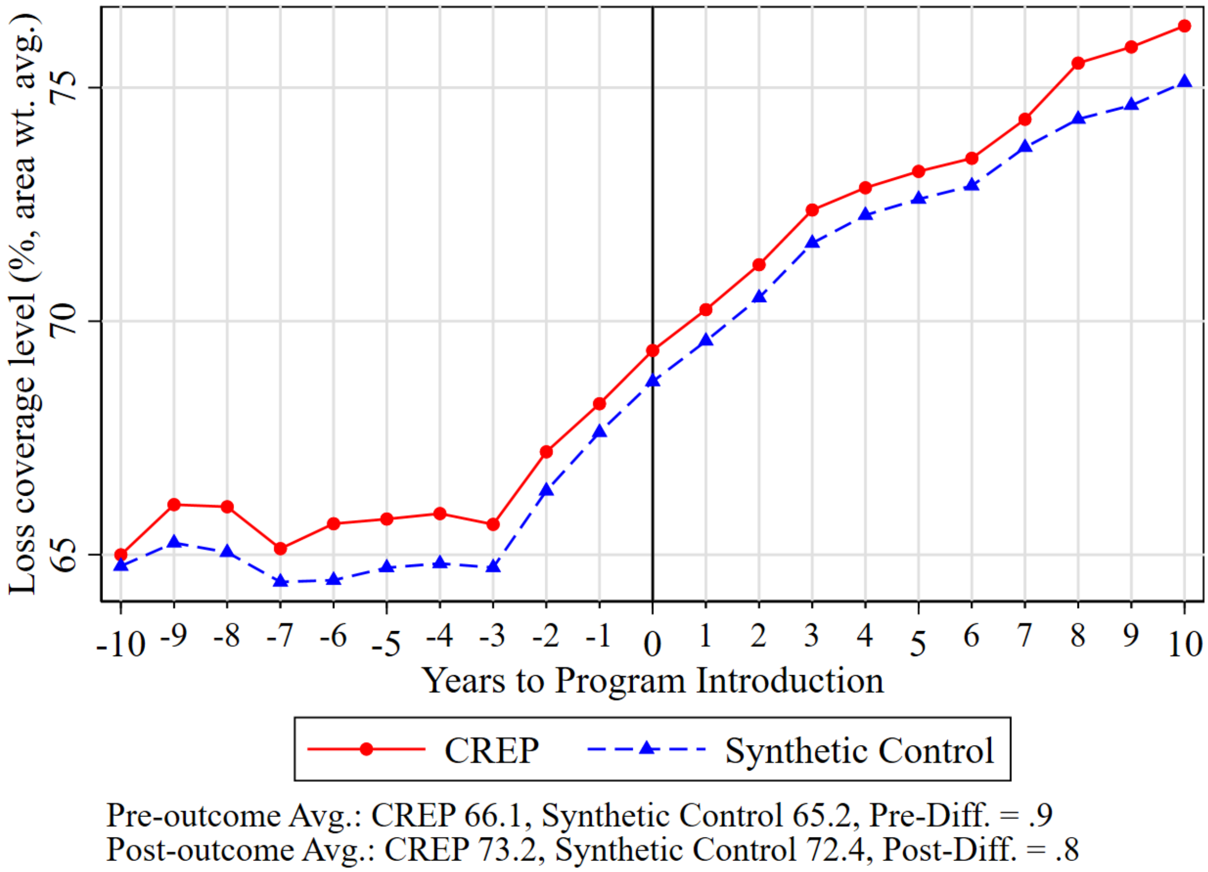


Figure A5. Trends in Insurance Coverage Level under the Federal Crop Insurance Program: Counties with CREP and Synthetic Controls

Notes: The graph shows how the coverage level for acres insured under the federal crop insurance program has changed by event time (x-axis) for both 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of 150 counties without CREP. The y-axis represents the acreage-weighted average of the county-level coverage level.

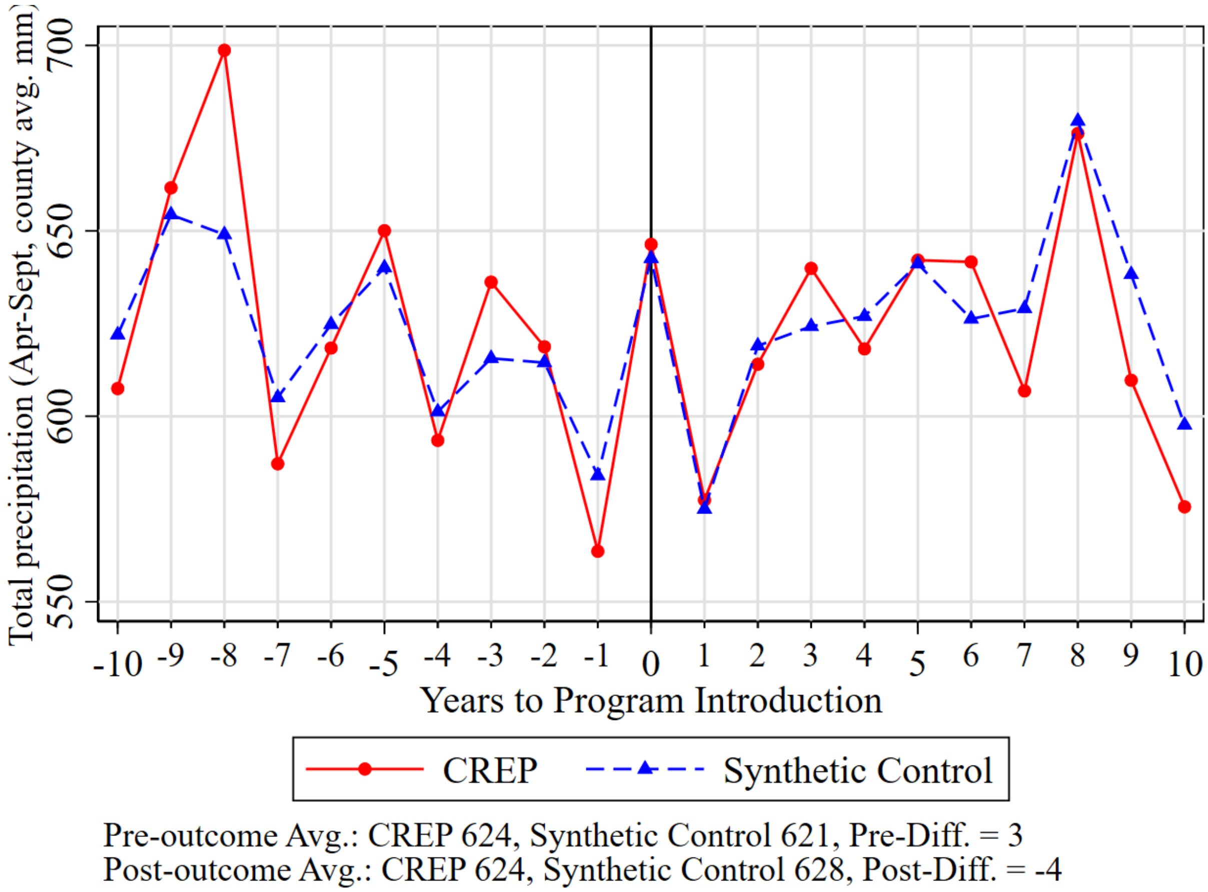
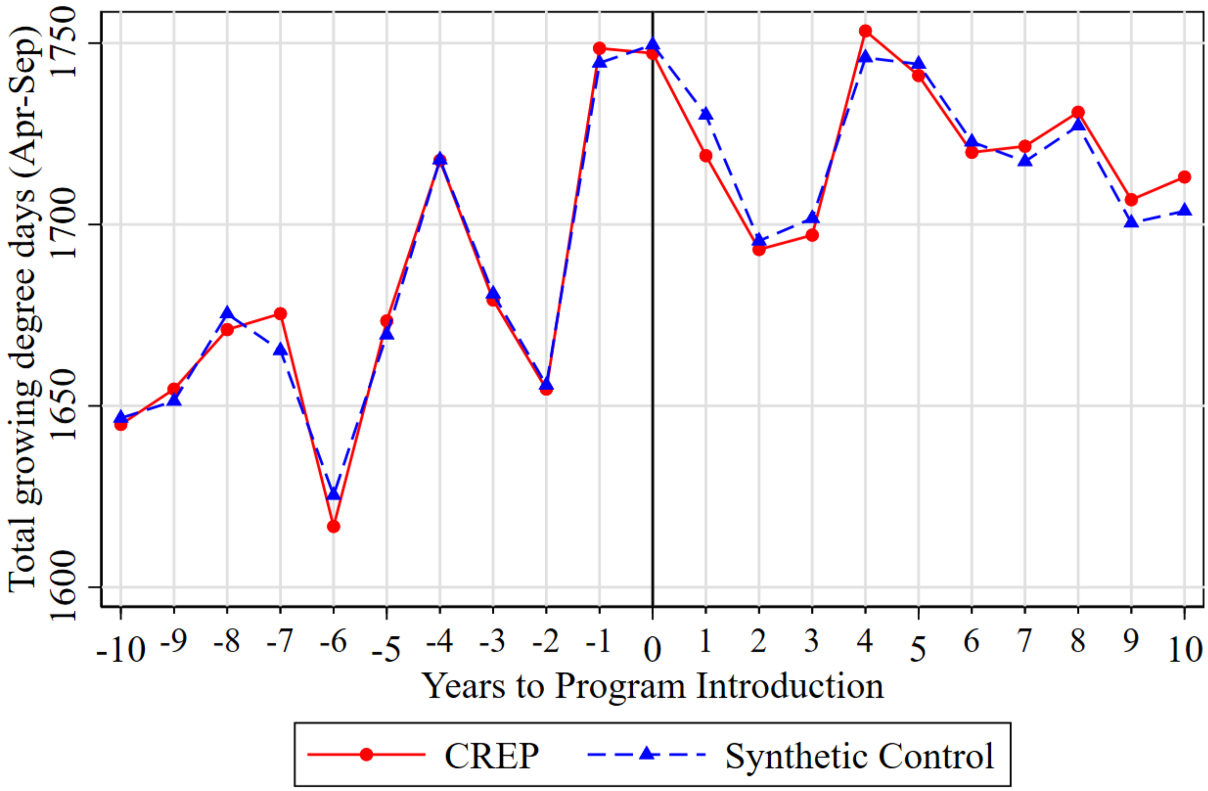


Figure A6. Trends in Precipitation during Crop Growing Season: Counties with CREP and Synthetic Controls

Notes: The graph shows trends in county-level average total precipitation (mm) during the crop growing season (April-September) (y-axis) by event time (x-axis) for both 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of 150 counties without CREP.



Pre-outcome Avg.: CREP 1674, Synthetic Control 1673, Pre-Diff. = 1
Post-outcome Avg.: CREP 1722, Synthetic Control 1722, Post-Diff. = 0

Figure A7. Trends in Growing Degree Days (10-29 Celsius) during Crop Growing Season: Counties with CREP and Synthetic Controls

Notes: The graph shows trends in county-level average growing degree days during the crop growing season (April-September) (y-axis) by event time (x-axis) for both 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of 150 counties without CREP.

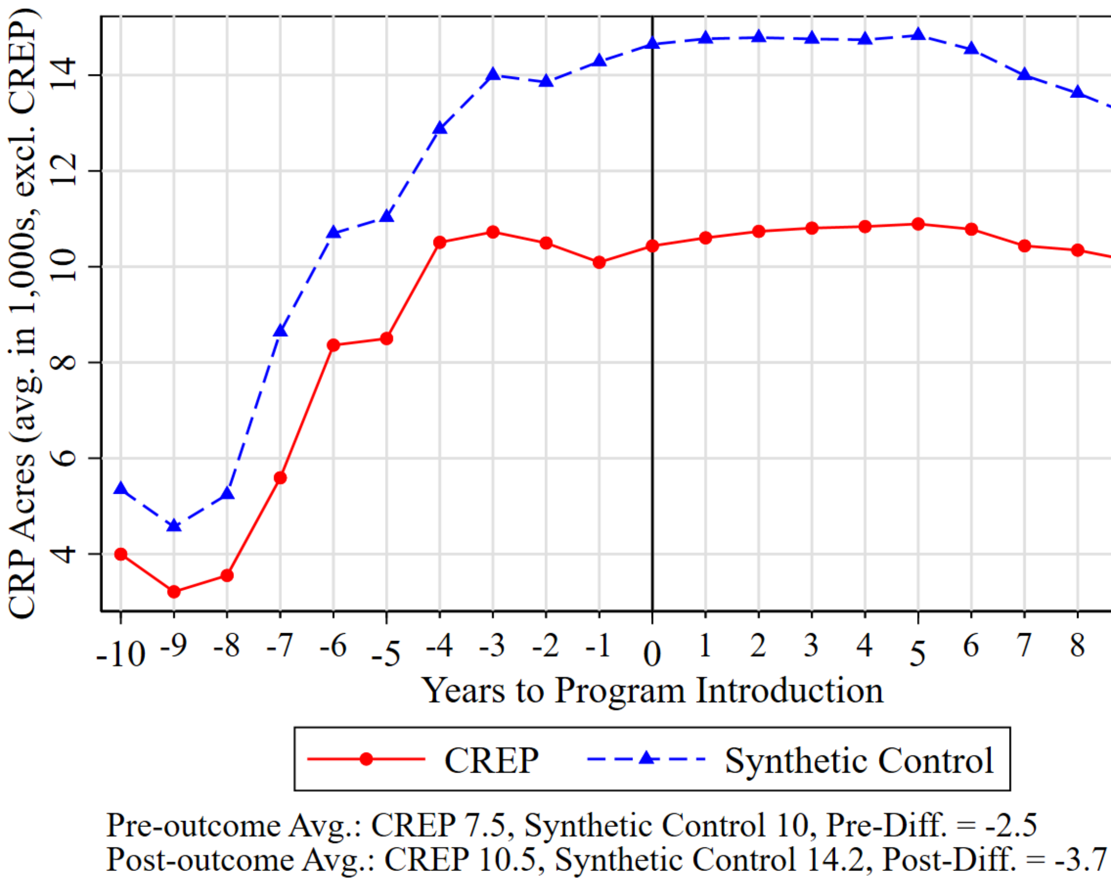


Figure A8. Trends in Acreage enrolled under the Conservation Reserve Program (excluding CREP) : Counties with CREP and Synthetic Controls

Notes: The graph shows trends in county-level average acres enrolled under Conservation Reserve Program, excluding CREP, (y-axis) by event time (x-axis) for both 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of 150 counties without CREP.

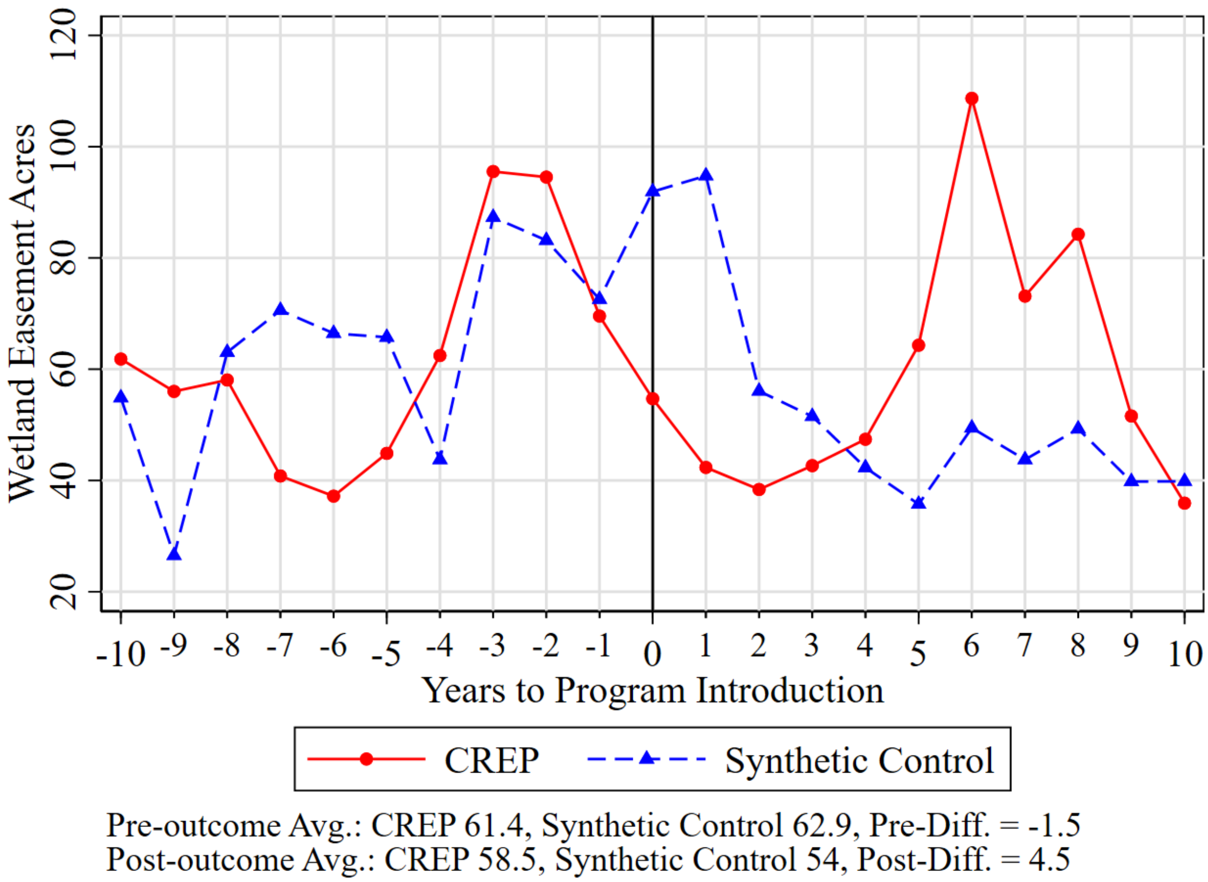


Figure A9. Trends in Acreage enrolled under the Agricultural Conservation Easement Program's Wetland Reserve Easement: Counties with CREP and Synthetic Controls

Notes: The graph shows trends in county-level average acres enrolled under the Wetland Reserve Easement component of the Agricultural Conservation Easement Program (y-axis) by event time (x-axis) for both 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of 150 counties without CREP.

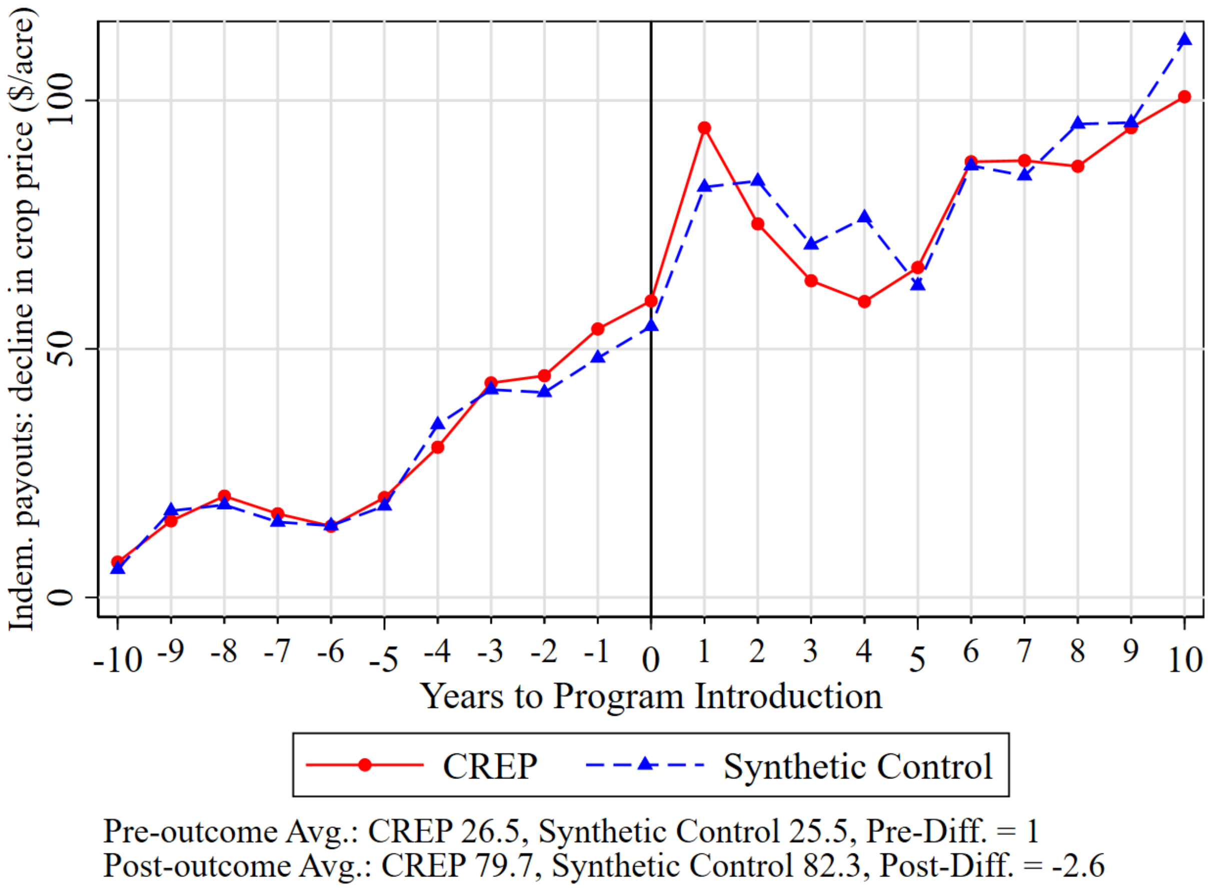


Figure A10. Trends in Indemnity Payouts due to Decline in Crop Price: Counties with CREP and Synthetic Controls

Notes: 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 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of 150 counties without CREP.

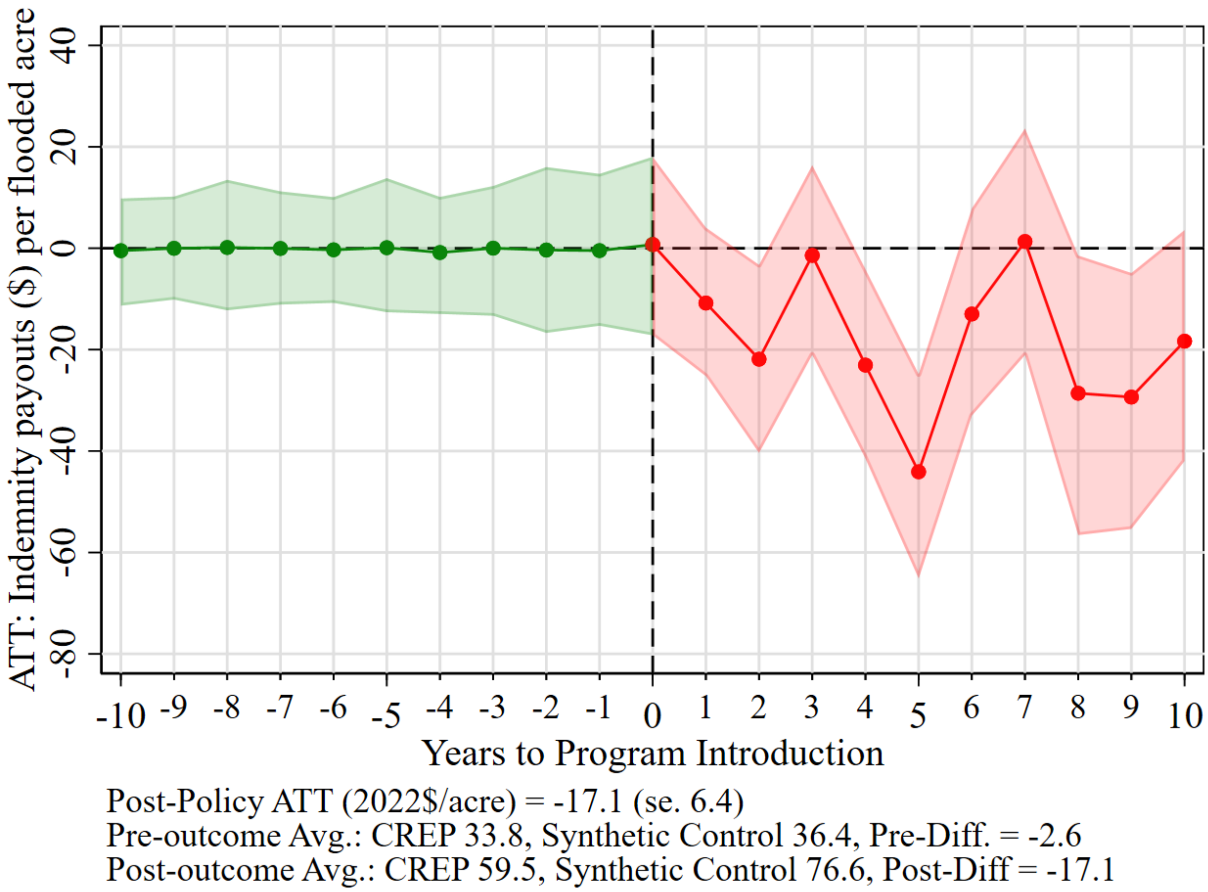
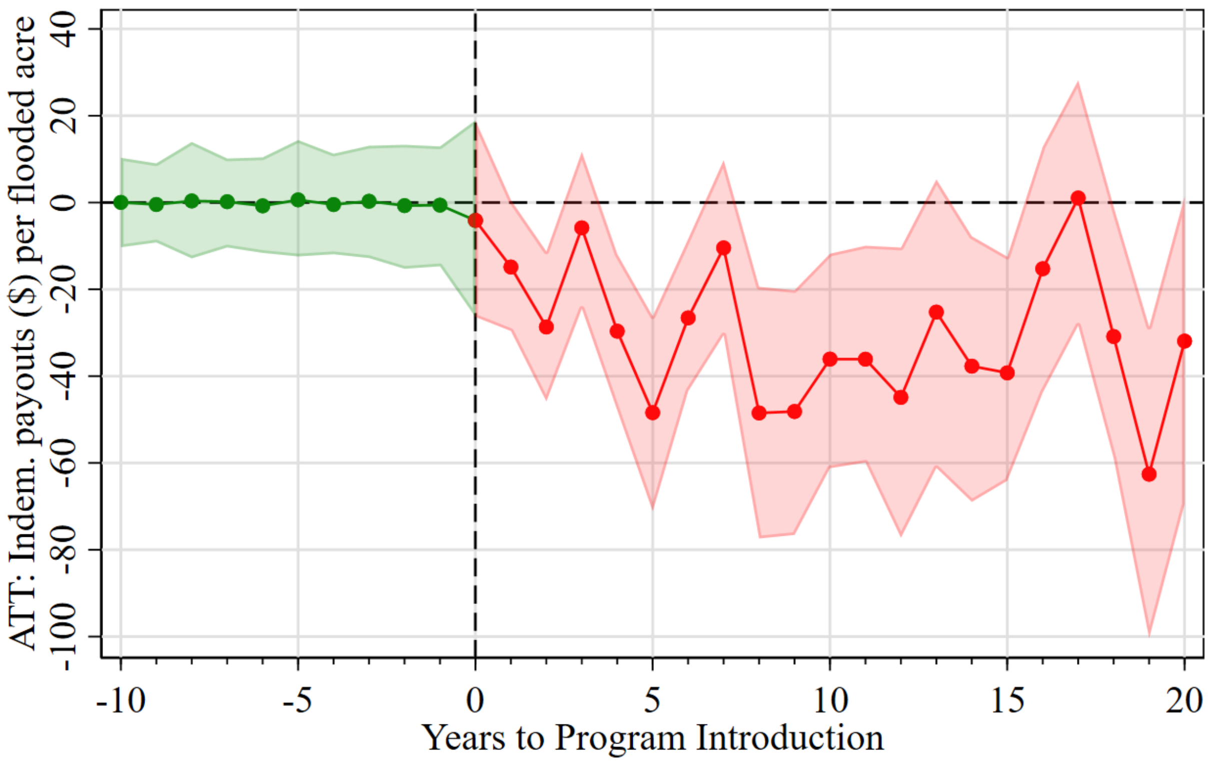


Figure A11. Estimated Impact of CREP Introduction on Flooded Crop Loss (ATT: no weather covariates)

Notes: 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 250 counties with CREP and their synthetic controls constructed based on a weighted average of 150 counties without CREP. Only lagged outcomes are used in choosing weights of untreated and not-yet treated counties to construct synthetic controls. Confidence intervals (95%) are constructed using wild bootstrap.



Post-Policy ATT (2022$/acre) = -29 (se. 6.6)
Pre-outcome Avg.: CREP 62.3, Synthetic Control 63.9, Pre-Diff. = -1.6
Post-outcome Avg.: CREP 84.5, Synthetic Control 116.1, Post-Diff = -31.6

Figure A12. Estimated Impact of CREP Introduction on Flooded Crop Loss (ATT: up to 21 event times)

Notes: The graph shows the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss, measured by 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 250 counties with CREP and their synthetic controls constructed based on a weighted average of 150 counties without CREP. 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 untreated and not-yet treated counties to construct synthetic controls. Confidence intervals (95%) are constructed using wild bootstrap.

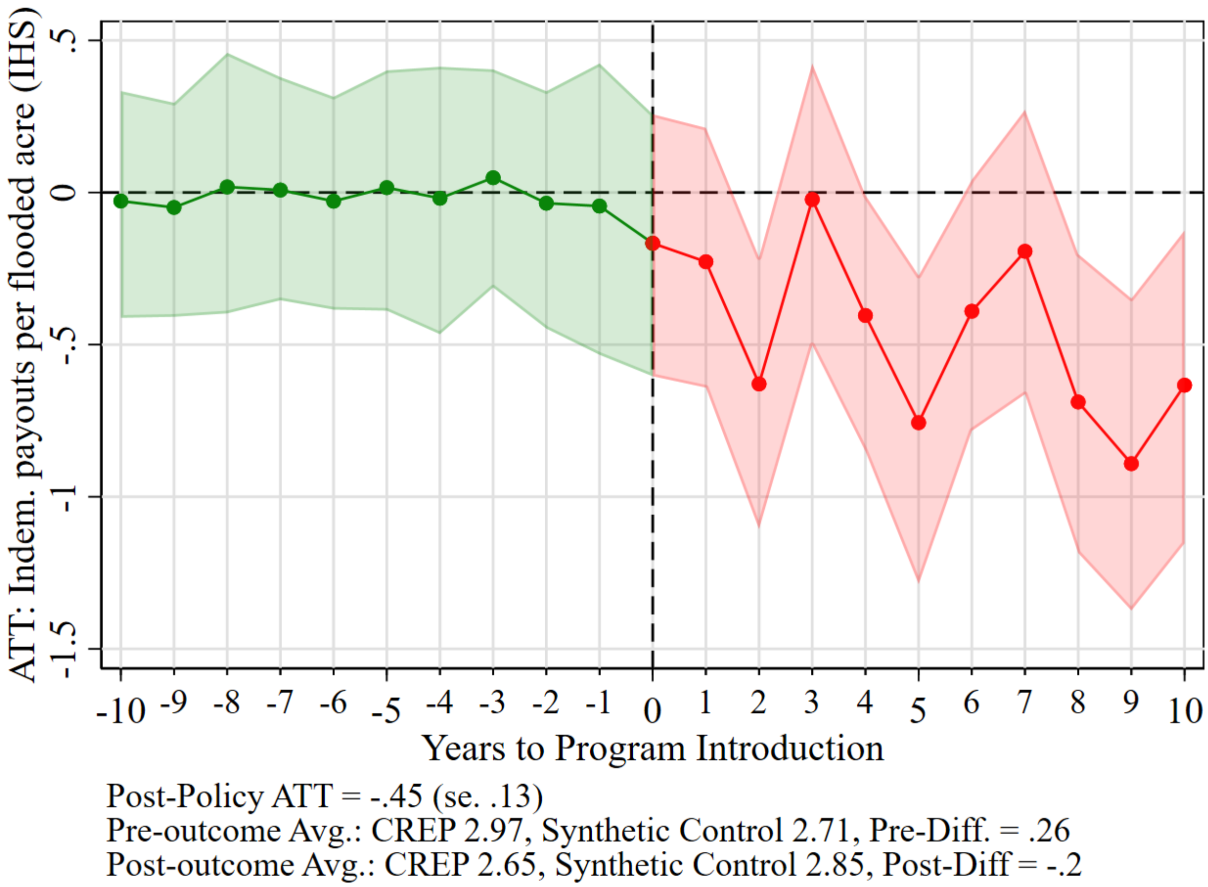


Figure A13. Estimated Impact of CREP Introduction on Flooded Crop Loss (ATT: IHS)

Notes: 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 250 counties with CREP and their synthetic controls constructed based on a weighted average of 150 counties without CREP. 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 untreated and not-yet treated counties to construct synthetic controls. Confidence intervals (95%) are constructed using wild bootstrap.

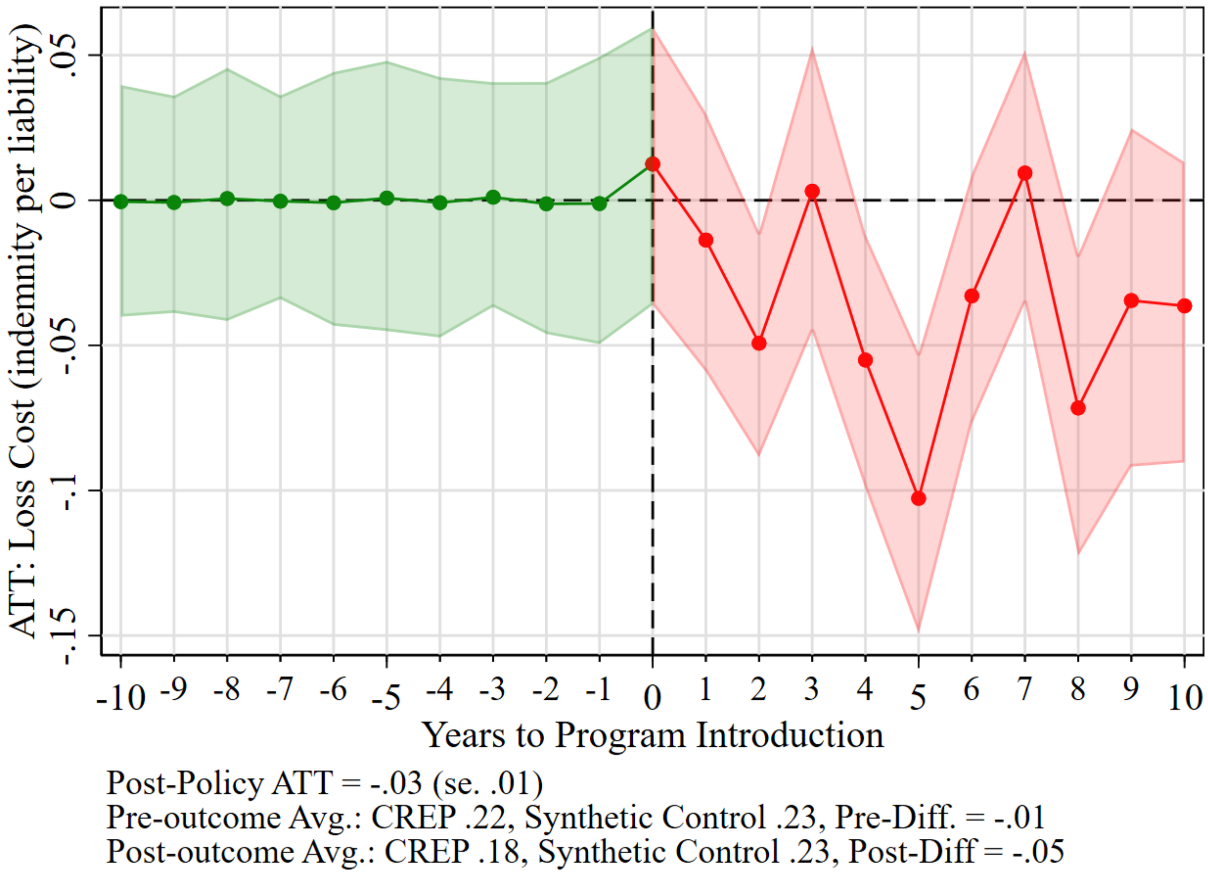


Figure A14. Estimated Impact of CREP Introduction on Flooded Crop Loss (ATT: Loss Cost)

Notes: The graph shows the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss, measured by loss cost (indemnity payouts per liability, 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 250 counties with CREP and their synthetic controls constructed based on a weighted average of 150 counties without CREP. 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 untreated and not-yet treated counties to construct synthetic controls.

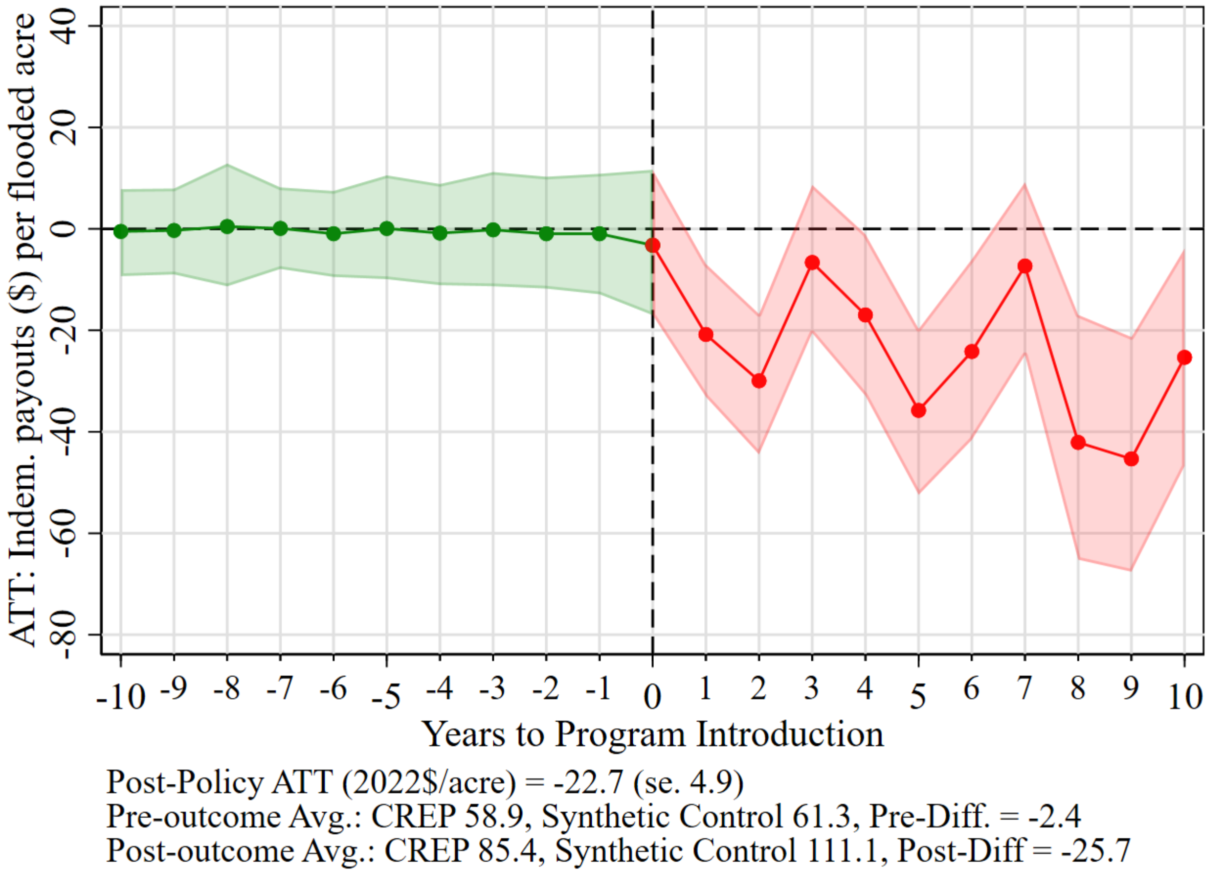


Figure A15. Estimated Impact of CREP Introduction on Flooded Crop Loss (ATT: alternative screening criteria for the analysis counties)

Notes: The graph shows the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss, measured by 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 363 counties with CREP and their synthetic controls constructed based on a weighted average of 272 counties without CREP. 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 untreated and not-yet treated counties to construct synthetic controls.

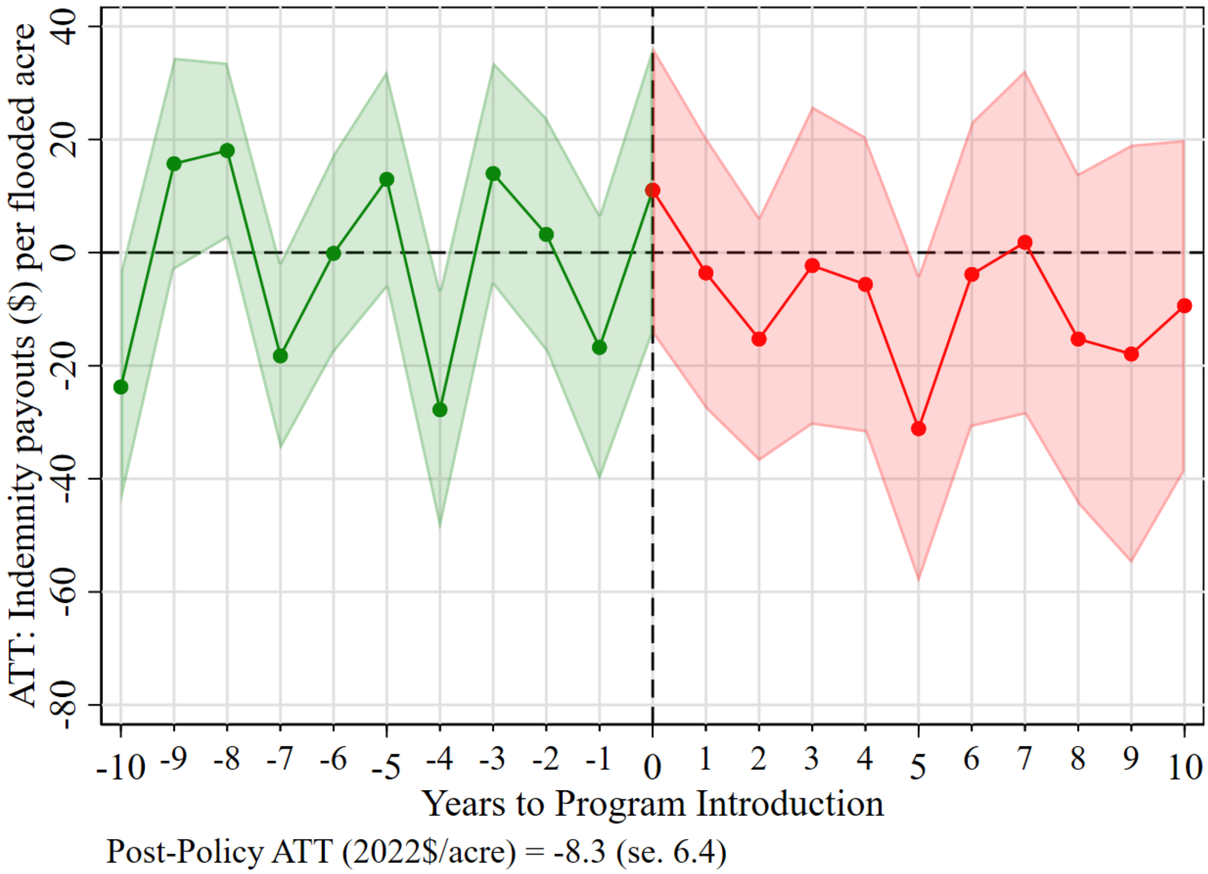


Figure A16. Estimated Impact of CREP Introduction on Flooded Crop Loss (ATT: Callaway and Sant'Anna (2021) without weather covariates)

Notes: The graph shows the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss, measured by indemnity payouts per flooded acre (2022$/acre, y-axis), across event time (x-axis) with 95 percent confidence intervals. The average program effect is estimated using the doubly robust estimator proposed by Callaway and Sant'Anna (2021) without covariates. Simultaneous confidence bands (95%) are constructed using multiplier bootstrap for statistical inference.

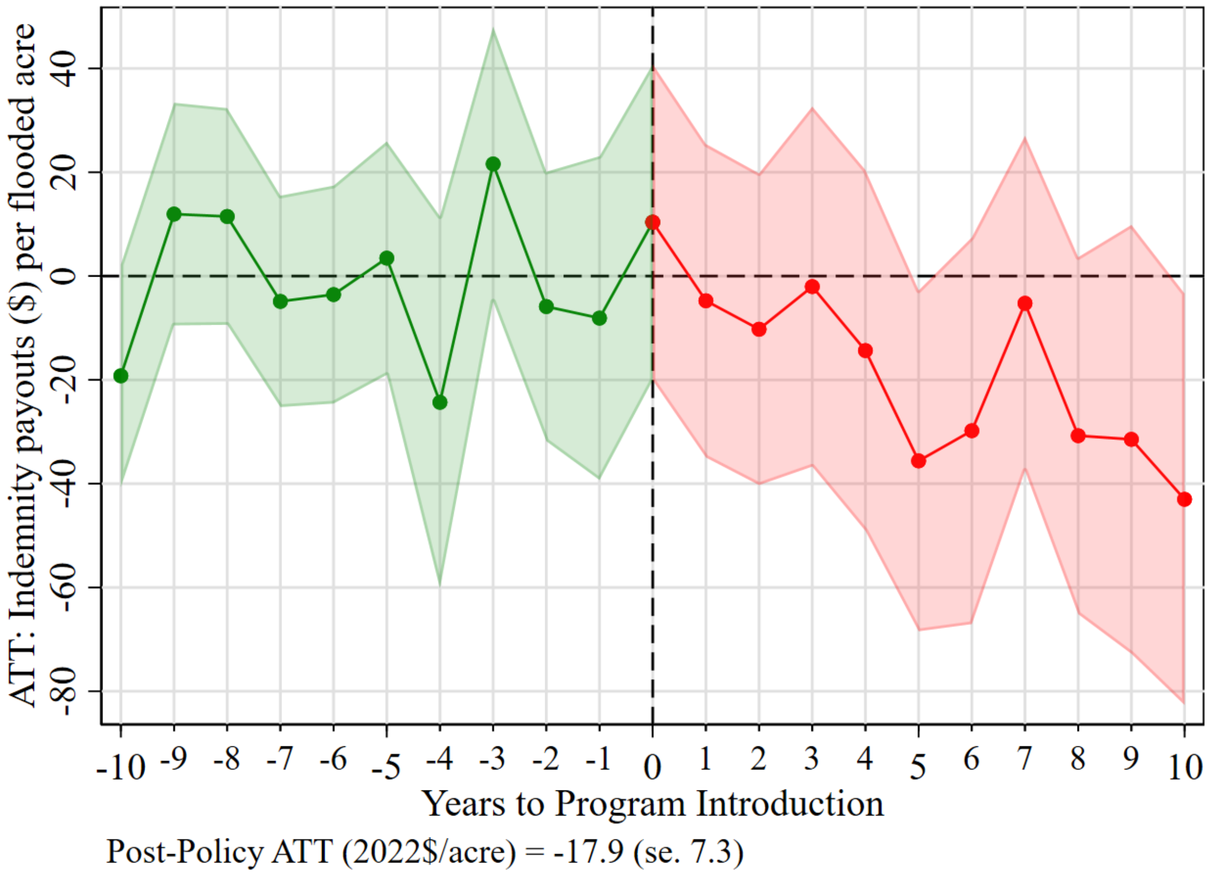


Figure A17. Estimated Impact of CREP Introduction on Flooded Crop Loss (ATT: Callaway and Sant'Anna (2021) with weather covariates)

Notes: The graph shows the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss, measured by indemnity payouts per flooded acre (2022$/acre, y-axis), across event time (x-axis) with 95 percent confidence intervals. The average program effect is estimated using the doubly robust estimator proposed by Callaway and Sant'Anna (2021) with weather covariates. Weather covariates include precipitation (mm) and growing degree days during the post-harvest (October to March) and crop growing seasons (April to September). Simultaneous confidence bands (95%) are constructed using multiplier bootstrap for statistical inference.

APPENDIX B. SYNTHETIC CONTROL METHOD: SUPPLEMENTARY MATERIALS

The empirical methodology employed to estimate the causal impact of CREP introduction on flooded crop loss utilizes a partially pooled synthetic control method with an intercept shift. This approach estimates the counterfactual trajectory of an 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. The method considers two imbalance measures to achieve this objective: (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) (Doudchenko & Imbens, 2016; Ferman & Pinto, 2021; Ben-Michael et al., 2022).

To be specific, let $\gamma_{ij} \geq 0$ denote the weight on untreated 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 untreated counties and $\Gamma = [\gamma_1, \ldots, \gamma_J] \in \Delta^{scm}$ be an N-by-J weight matrix where $\Delta^{scm} = \Delta_1^{scm} \times \ldots \times \Delta_J^{scm}$. The untreated counties consist of both counties where PES program was never available during the analysis 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 $q^{sep}(\Gamma)$:

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

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

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

where $L \equiv max_{j\leq J}L_j$. In cases where all treated units can find a perfect synthetic control unit ($q^{sep}(\Gamma) = 0$), a perfect fit for the average outcome trend of the treated group is achieved ($q^{pool}(\Gamma) = 0$). However, in practice, not all treated units have an imperfect pre-treatment fit, resulting in a gap in the average pre-trend outcome between the treated and synthetic controls, which undermines the validity of the estimated average program effect.

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

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

where the relative importance of the average outcome fit (pooled fit) to individual outcome fit increases with parameter $\nu \in [0,1]$.[14] To ensure unique weights and avoid interpolation biases, a regularization penalty term λ is added (Abadie et al., 2015; Doudchenko & Imbens, 2016; Abadie & L'Hour, 2021; Arkhangelsky et al., 2021).[15] 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:

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

Using the set of weights $\hat{\gamma}_{ij}$ obtained from the equation (B.3), I estimate the counterfactual average outcome of county j treated in year T_j at event time k as follows:

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

where the intercept shift represents the average pre-policy outcome difference between treated county j and its synthetic control county. By combining equations (B.5) with (8), I obtain the form of the weighted DID estimator $\hat{\tau}_{jk}$:

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

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

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[14] 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 $\gamma_1, \ldots, \gamma_J$ that minimizes the individual pre-policy fit only. See Ben-Michael et al (2022) for details.

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

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