Payments for Ecosystem Services Programs and Climate Change Adaptation in Agriculture

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Abstract

Payments for ecosystem services (PES) programs can mitigate economic losses from extreme weather by establishing natural infrastructure. This paper examines the flood-mitigation benefits of the U.S. Conservation Reserve Enhancement Program (CREP), which was originally launched to improve downstream water quality and wildlife habitat through wetland and riparian buffer restoration. Leveraging spatial and temporal variation in CREP introduction across counties, I show that the program reduced both the number of flooded crop acres and the severity of loss on those acres, significantly lowering crop insurance indemnity payouts. Potential mechanisms include the retirement of flood-prone cropland and flood-protection services from nature recovery.

Keywords: payments for ecosystem services, nature-based solutions, climate change adaptation, natural disasters, 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). Global efforts to mitigate and adapt to climate change are increasingly focused on restoring natural infrastructure, such as forests and wetlands, which often requires land use changes for agricultural land (e.g., Nature-Based Solution Roadmap at COP 27, Global Goal on Adaptation at COP 28, 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; Karwowski, 2022; 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). Despite these potential benefits, relatively little is known about the cost-effectiveness of implementing PES programs that invest in such natural infrastructure as strategies for climate change adaptation.

This study examines the extent to which the introduction of a large-scale PES program mitigates economic losses during extreme weather events, focusing on the flood-mitigation benefits of the Conservation Reserve Enhancement Program (CREP) in the United States. Since its establishment in 1997, CREP has invested $1.6 billion to establish conservation cover on 1 million acres of agricultural land nationwide between 2013 and 2022 (USDA-FSA, 2023). The program was initially introduced to reduce agricultural nonpoint source water pollution and to restore wildlife habitat by converting environmentally sensitive cropland and marginal pastureland near water bodies into riparian buffers and wetlands. These conservation practices are highly

effective in filtering nutrient runoff and improving wildlife habitat quality but also have the potential to substantially reduce regional flood risks.

I begin with a theoretical analysis describing two mechanisms through which 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.

In an ideal experiment for assessing the flood-mitigation benefits of PES program, we would compare flood damage on cropland between counties that are identical in all respects, except for the PES program availability. However, my identification strategy faces two empirical challenges. First, the introduction of PES program may be associated with other factors that contribute to flood damage on cropland. For example, the government may introduce the program in regions vulnerable to frequent flooding on cropland to reduce nutrient and pesticide runoff. Second, the variation in the timing of program 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 exploits county-level spatial and temporal variation in the introduction of CREP and flood damage on cropland across 387 counties in the Mississippi River Basin from year 1989 to 2022. The analysis utilizes administrative data on CREP and flood-related crop losses obtained from the United States Department of Agriculture (USDA)'s Farm Service Agency (FSA) and Risk Management Agency (RMA). 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, 2024; 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 first implement the latter approach and construct a comparison group for each county with CREP using 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, using counties that (i) never or not-yet introduced CREP but (ii) had 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 introduction. I then complement the analysis with the heterogeneity-robust event-study estimator proposed by de Chaisemartin & D'Haultfoeuille (2024) to examine pre-trend placebo effect, policy anticipation effect, and the robustness of the findings.

Key identification assumptions include the absence of time-varying confounding factors, policy anticipation, and 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 national environmental and resource concerns, such as declining wildlife habitat in Corn Belt region or nutrient pollution in the Gulf of Mexico, rather than county-specific trends in flood-related crop losses. Second, farmers have little incentive to manipulate or adjust their crop losses in anticipation of CREP introduction, given the unpredictability of flood events and the program's stringent eligibility requirements on cropping practice and history. Finally, the estimated program effects are robust to excluding non-CREP counties that border CREP counties from the comparison group, indicating that spatial spillovers do not significantly influence the estimated impacts.

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 36.8 percent and mitigated the severity of crop damage on those acres by 25.1 percent during the initial 11 years of program implementation. The estimated program effects suggest that the introduction of CREP reduced $105 million (in 2022 USD) of flood-related crop losses and saved $76 million in indemnity payouts that would have been paid to the insured farmers in the absence of the

program during the same period. Under strong assumptions on the flood risk of crop acres enrolled in the program, 41 percent of these benefits stem from the removal of flood-prone cropland from production (the conversion effect), while the remaining 59 percent arise from the flood-protection services provided by conservation cover that reduce the severity of flood damage on cropland that remains in production (the protection effect).

The magnitude of flood-mitigation benefits varies spatially and temporally. The descriptive evidence suggests that benefits tend to be greater in counties that (i) participate more extensively in CREP, leading to a greater extent of natural-infrastructure restoration; (ii) rely heavily on crop insurance to manage production risk; (iii) are located further downstream in the Mississippi River Basin, where flood exposure is inherently higher; (iv) have extensive cropland located within the 100-year floodplain; and (v) have limited flood protection for cropland from engineered flood-control infrastructure, such as levees.

This study contributes to the growing literature on climate change adaptation in agriculture and to global efforts that employ PES programs to restore ecosystems for enhanced climate resilience. Prior studies identified a lack of adaptation in agriculture and projected substantial losses in agricultural productivity 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; Ortiz-Bobea, 2021). Existing research also has shown that floodplain conservation and wetlands can mitigate flood damages (Kousky and Walls, 2014; Karwowski, 2022; Taylor & Druckenmiller, 2022). This study extends the literature by shifting the focus from the benefits of natural infrastructure to the causal impact of introducing a large-scale PES program that finances the restoration of such infrastructure. Identifying such policy-induced adaptation benefits is challenging because PES programs are rarely introduced in ways that generate quasi-experimental variation. By documenting and leveraging the staggered rollout of CREP in one of the most productive agricultural regions in the world, this study provides robust causal evidence that introducing PES programs can reduce economic losses from weather anomalies through the establishment of natural infrastructure. To my knowledge, this is the first economic analysis that exploits this policy variation and estimates the adaptation benefits in agriculture associated with the introduction of CREP, which has invested billions of dollars in restoring natural infrastructure nationwide since 1997.

This study also contributes to a broader understanding of how environmental policy interacts with disaster risk management policy (Fischer & Preonas, 2010; Ifft et al., 2019; Fleming et al., 2020). For instance, the U.S. federal agricultural conservation program and 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). Given their scale, it is important for policymakers to understand how these two major policy instruments interact. Previous studies have mainly examined this interaction from one direction: how heavily subsidized crop insurance (i) 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) and (ii) 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 introducing an environmental policy aimed at land conservation can reduce production risks and lower the financial burden on existing risk management programs.

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 research and policy should also consider (i) the long-term benefits of PES programs in building resilience against adverse weather events and (ii) the economic spillover effects on disaster assistance 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). For instance, this study supports incorporating information from federal conservation programs into crop insurance premium calculations (Woodard et al., 2012; Woodard & Verteramo-Chiu, 2017). Recently, several Midwestern states (Iowa, Indiana, and Illinois) started to offer insurance premium discounts for cropland planted with cover crops (i.e., conservation cover) before the subsequent crop season. Similar premium discounts could be considered for practices that enhance streambank protection and restore wetlands.

The remainder of this study is organized as follows. Section 2 provides institutional context on flood risk management, PES programs, and the U.S. federal crop insurance program. Section 3 introduces the theoretical framework, which derives the mechanisms through which the introduction of PES programs can mitigate economic losses in agriculture under extreme weather events. Section 4 presents the data and discusses 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 discusses the empirical findings, followed by falsification and placebo tests, heterogeneity analysis, and the decomposition of benefits. Section 7 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 $6 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

[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

levees in upstream areas, however, may displace the force of floodwaters downstream and generate negative spillover effects, 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 habitat, 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).

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, with the goal of protecting ecosystems and promoting 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 (AES) 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-FSA in collaboration with the USDA-Natural Resources Conservation Service (NRCS) and is funded by the Commodity Credit Corporation (CCC) through partnerships with local, state, and federal governments. The introduction of CREP varies both spatially and temporally across counties, reflecting differences in regional environmental concerns and the nature of federal-state partnerships regarding program implementation and cost-sharing arrangements.

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 focuses on restoring filter strips, riparian buffers, and wetlands in major tributary states, such as Iowa, Illinois, Minnesota, and Ohio, with the goal of reducing agricultural nonpoint source pollution entering the Gulf of Mexico and enhancing wildlife habitat. Since 1997, federal and state governments have identified watersheds in the Corn Belt that contribute to downstream water quality degradation and have introduced CREP in counties within those watersheds. Nationally, CREP allocated $154 million in annual payments to establish and maintain approximately 800,000 acres of conservation practices on agricultural land in the fiscal year of 2022 (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. For instance, 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 very high risk of loss and reduce farmer's incentive to change cropping behavior in anticipation of the program introduction. By enrolling in the program, landowners restore filter strips, riparian buffers, and wetlands on their eligible land in exchange for program payments.

As in many existing PES programs, payments in CREP are structured to compensate for the cost of adopting conservation practices (pay-for-effort), including one-time upfront payment and recurring 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-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-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 much higher for land use conversion practices, such as the restoration of riparian buffers and filter strips on cropland under 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 U.S. 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, 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 develops 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 serves three primary purposes. First, it identifies the mechanisms through which PES programs reduce climate-related crop losses: (i) by converting at-risk cropland into conservation cover, which eliminates potential crop losses (the conversion effect), and (ii) by reducing the extent of damage on remaining cropland through the protection services of natural infrastructure established under the PES program (the protection effect). Second, it establishes a conceptual link between crop losses caused by extreme weather events and recorded crop insurance indemnity payouts, providing a theoretical foundation for interpreting insurance data in

[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/.

the empirical analysis. Finally, it generates empirically testable predictions regarding the loss mitigating benefits of PES programs and reveals key sources of heterogeneity in these effects.

The theoretical framework applies key insights from Ehrlich and Becker (1972) and Quaas and Baumgärtner (2008) to the empirical context of how PES programs reduce weather-related crop losses and insurance payouts. Self-insurance refers to costly actions that reduce the severity of a loss if a negative event occurs, whereas self-protection lowers the probability that the event occurs at all (Ehrlich & Becker, 1972). Drawing on the insurance function of ecosystem services (Quaas & Baumgärtner, 2008), I model land conservation practices as a form of self-insurance such that natural infrastructure established through PES programs reduces the severity of extreme weather impacts but does not significantly alter the probability of such events occurring at the scale of an individual farm.

Building on these foundations, the framework employs a two-state expected utility model in which a risk-averse farmer faces stochastic weather conditions that affect crop returns. The farmer maximizes expected utility by (i) allocating land between crop production and conservation under PES contract and (ii) adjusting the coverage level of crop insurance for cropland remaining in production, within an institutional setting where insurance is heavily subsidized but capped below full indemnity. PES payments incentivize the reallocation of cropland toward conservation by reducing expected crop losses through both the conversion and protection effects. Simultaneously, the insurance coverage level is determined by expected crop losses, the insurance markup, and the level of conservation investment.[3]

The theoretical framework relies on several simplifying assumptions. First, farmers are assumed to make land use and crop insurance decisions independent of the actions of their neighbors, based on their own individual preferences, land characteristics, and policy parameters. Second, farmers internalize within-farm spillover effects of conservation practices, recognizing that natural infrastructure in one part of a farm can influence outcomes elsewhere on the same farm, but they do not account for spillover effects across farms. Third, the framework adopts a static

[3] The two-state expected utility framework conceptualizes self-insurance through the establishment of natural infrastructure and market insurance as substitutable strategies for mitigating loss. This substitutability between self-insurance and market insurance is not a universal feature. Bourgeon and Picard (2024) showed that, when losses are multi-valued rather than binary, the relationship between the two forms of insurance can become complementary, particularly when self-insurance mitigates moderate but not catastrophic losses without significantly altering the probability of extreme events. While my framework abstracts from such loss heterogeneity for analytical tractability, this distinction has implications for interpreting behavioral responses to conservation and insurance incentives.

approach, abstracting from long-term dynamics such as potential adjustments in insurance premiums resulting from widespread ecosystem restoration following PES program implementation (Baumgärtner & Strunz, 2014; Quaas et al., 2019) or farmers delaying conservation practice adoption in anticipation of future PES payments (Pates & Hendricks, 2020).

3.1 Farmer's Land Use Decision

Consider a risk-averse farmer who allocates a fixed total cropland A into e acres for conservation practices and $A - e$ 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 net return of y per acre. On the other hand, cropland is susceptible to flooding (the "bad state") with a probability $q > 0$ that reduces the net crop return y by an amount D, with both q and D known to the farmer. In the event of flood-induced crop loss, an insurance policy covers a fraction ϕ ($0 \leq \phi \leq 1$) of the loss, leading to an indemnity payout of ϕD, with the farmer bearing the remaining fraction $(1 - \phi)D$. The crop insurance policy premium equals the expected indemnity payout with a markup factor m, $mq\phi D$, where the premium is actuarially fair when $m = 1$.

The farmer can choose to allocate a portion of cropland to conservation cover at a per-acre cost c and obtain associated private net benefits w, which may include erosion control, recreational and scenic amenities, stewardship satisfaction, or increased crop damage from wildlife, in addition to receiving per-acre monetary compensation $r > 0$ from a PES program. These private net benefits of conservation including PES program payment, $w + r - c$, are assumed to be constant regardless of the state of nature. In addition, the conservation acreage e functions as a form of self-insurance by mitigating the extent of loss D on the remaining cropland $A - e$ under the bad state with a diminishing marginal effect, $\frac{\partial D}{\partial e} \equiv D_e < 0$ and $\frac{\partial^2 D}{\partial e^2} \equiv D_{ee} > 0$.

[4] The fixed total cropland excludes the possibility of the farmer expanding their overall crop acreage in response to the introduction of PES programs for working cropland. 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 4-6 years of 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 crop acreage $A - e$ and conservation acreage e under the bad state and good state, respectively. Then, the risk-averse farmer chooses the conservation acreage e and the coverage level ϕ to maximize expected utility V, considering the two possible states of nature:

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

where:

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

and:

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

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

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

Given the diminishing marginal utility of income (such 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 loss coverage under the bad state (LHS of condition 2) outweighs that from higher premium costs in both states (RHS of condition 2). If the premium is actuarially fair or subsidized ($m \leq 1$), then the farmer would fully insure crop loss under the bad state ($\phi = 1$) at any conservation acreage e because the marginal utility of additional coverage in the bad state exceeds its marginal premium cost for all e (i.e., $U'(\pi_1) \geq m[qU'(\pi_1) + (1-q)U'(\pi_0)]\ \forall e$). In fact, the U.S. federal crop insurance program heavily subsidizes crop insurance ($m < 1$), so full insurance would be optimal for the farmer. However, the crop insurance program typically imposes upper limits on indemnity coverage (e.g., individual yield or revenue coverage cap of 75 to 85 percent in the U.S. federal crop insurance program). Thus, the farmer's optimal coverage level is fixed at the maximum attainable level offered by the program ($\phi^* = \phi^{\max} < 1$) at any conservation acreage e.

The optimal conservation acreage e^* satisfies the first-order necessary condition:[5]

[5] The concavity of the farmer's objective function V with respect to conservation acreage e is shown as:

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

because

$$\frac{\partial V}{\partial e} \equiv [qU'(\pi_1) + (1-q)U'(\pi_0)]\left\{w + r - c - \underbrace{mq\phi^{\max}[D(e^*) - D_e(A-e^*)]}_{\text{savings in insurance premium}}\right\} \tag{3}$$

$$\underbrace{+U'(\pi_1)q(1-\phi^{\max})[D(e^*) - D_e(A-e^*)]}_{\text{loss mitigating benefits of conservation}} \leq y[qU'(\pi_1) + (1-q)U'(\pi_0)].$$

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 also increase net return from conservation and reduce expenditure on insurance premiums for both crop acreage converted into conservation and remaining crop acreage. The additional conservation acreage would also contribute to mitigating crop loss in the bad state. The optimal conservation acreage under PES contract increases in the net private benefits of conservation and in the loss-mitigating benefit of conservation, which depends on flood risk and damage. As a result, enrollment is selective: farms with low opportunity cost of conservation or high within-farm flood mitigation benefits are more likely to participate in the PES program with larger conservation acreage.

3.2 Loss Mitigating Benefits of PES Programs

It is straightforward to show that additional financial incentives r offered by the PES program encourage the farmer to expand conservation acreage. The optimal conservation acreage e^* increases with the program payment r:[6]

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

Introducing PES program payments r potentially reduces the expected crop loss, $qD(e^*)(A - e^*)$, through two channels:

$$\frac{\partial^2 \pi_1}{\partial e^2} \equiv [-(1-\phi)D_{ee} - m\phi q D_{ee}](A-e^*) - 2[-(1-\phi)D_e - m\phi q D_e] < 0,$$

and

$$\frac{\partial^2 \pi_0}{\partial e^2} \equiv -m\phi q D_{ee}(A-e^*) + 2m\phi q D_e < 0.$$

[6] Let ρ be the farmer's coefficient of constant absolute risk aversion (i.e., $-\rho U'(\cdot) = U''(\cdot)$). Then,

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

$$\frac{\partial qD(e^*)(A-e^*)}{\partial r} \equiv q\left[\underbrace{\frac{\partial(A-e^*)}{\partial r}D(e^*)}_{\text{conversion effect}} + \underbrace{(A-e^*)D_e\frac{\partial e^*}{\partial r}}_{\text{protection effect}}\right] < 0, \quad (5)$$

because $\frac{\partial e^*}{\partial r} > 0$ and $D_e < 0$. Condition (5) identifies two mechanisms through which PES programs mitigate crop loss. The first is the conversion effect, which operates by converting at-risk cropland into conservation use and removing it from exposure to potential damage. This direct reduction in cultivated area lowers the number of crop acres that could potentially be damaged by adverse weather events, such as flooding. In addition, because farmers with higher expected losses are more likely to enroll in PES programs (as implied by condition 3), the conversion effect also likely changes the composition of remaining cropland toward land with lower inherent flood risk or loss severity. Consequently, the conversion effect reduces both the number of damaged acres and the average severity of damage in regions where PES programs are implemented.

The second mechanism is the protection effect, which arises because conservation cover established under PES programs provides ecosystem services, such as flood control service from wetlands or riparian buffers, that reduce the extent and intensity of damage on the remaining cropland. To clarify the mechanisms within the protection effect, suppose that the aggregate damage function can be expressed as $D(e) = p(e)s(e)$, where $p(e) \in [0,1]$ denotes the fraction of remaining cropland acres that incur damage ($p_e < 0$), and $s(e) > 0$ represents the average loss per damaged acre ($s_e < 0$). Then, the protection effect term in condition (5) can be decomposed as:

$$\underbrace{q(A-e^*)D_e\frac{\partial e^*}{\partial r}}_{\text{protection effect}} \equiv \underbrace{q(A-e^*)p_e(e^*)s(e^*)\frac{\partial e^*}{\partial r}}_{\text{reduced crop area damaged}} + \underbrace{q(A-e^*)p(e^*)s_e(e^*)\frac{\partial e^*}{\partial r}}_{\text{reduced severity of damage}} < 0. \quad (6)$$

The first term reflects a reduction in the cropland area damaged, while the second captures a reduction in the expected loss per damaged acre. Thus, the protection effect also reduces both the number of damaged acres and the average severity of damage through the protection services provided by conservation cover established under PES programs.

Given that the crop insurance policy compensates a fixed portion ϕ^* of realized crop losses in terms of area and quality, these loss-mitigating effects of PES programs directly translate into lower insurance indemnity payouts. The reduction in indemnities operates through the same two mechanisms identified above. The conversion effect eliminates potential indemnity payouts on

cropland that has been retired from production and enrolled in conservation, while the protection effect lowers the expected indemnity payouts on the remaining insured cropland under adverse weather conditions. Thus, I have:

Proposition. *The introduction of payments for ecosystem services programs reduces crop insurance indemnity payouts by establishing natural infrastructure that mitigates weather-related crop losses.*

This proposition motivates an empirical examination of the flood-mitigation benefits of CREP and the relative magnitude of conversion and protection effects. Conditions (5) and (6) suggest two primary flood outcomes of interest: (i) the number of flooded crop acres and (ii) the severity of loss per flooded crop acre. It also identifies key sources of effect heterogeneity across farmers and regions, including the probability of flooding events, the extent of per-acre losses when such events occur, the effectiveness of conservation practices in mitigating such losses, the additional conservation acreage induced by CREP, the remaining cropland protected by the established natural infrastructure and crop insurance policies.

In the empirical analysis that follows, I examine spatial heterogeneity of the estimated program effects along these theoretical dimensions. For instance, in flood-prone areas, such as the downstream regions of the Mississippi River Basin, reallocating cropland to conservation cover can substantially reduce flood-related damages and associated insurance claims. Likewise, areas with higher participation in PES programs and higher crop insurance coverage levels are expected to experience larger reductions in indemnity payouts. On the other hand, in crop regions already protected by engineered flood controls, such as levees, the benefits of PES-induced natural infrastructure may be more limited. Overall, the theoretical results suggest that PES programs can lessen the economic impacts of extreme weather on agriculture, with the magnitude of these benefits varying across spatial, climatic, and institutional contexts.

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 timing of CREP introduction, acres enrolled in the program by practice type, and program payments from 1989 to 2022. The CREP data are reported by fiscal year, whereas the crop loss data follow crop year, defined as the calendar year in which

the crop is harvested. To align the two, CREP introduction years are shifted one year earlier in the county-by-year panel. For example, fiscal year 1998, which spans October 1997 through September 1998, is matched with crop year 1997 for two reasons. First, conservation practices established under CREP in the early fiscal year 1998 may influence flooding outcomes for crops harvested in crop year 1997. Second, shifting CREP introduction by one year helps mitigate anticipation effects, as landowners may adjust land-use decisions in response to information about an upcoming program introduction. Thus, CREP data are lagged by one year, and all references to "year" in this paper refer to calendar year rather than fiscal year.

Because CREP was introduced at different times across counties, a panel that is balanced in calendar time becomes unbalanced in event time (years since program introduction). This imbalance implies that event-time estimates may vary mechanically with changes in the composition of treated counties rather than reflecting true dynamic program effects. To address this concern, the empirical analysis primarily focuses on counties in which CREP was introduced between 1997 and 2010, which generates a balanced event-time panel for the first 11 years since program introduction. Given that most land-use conversion CREP contracts span 10 to 15 years, and that initial enrollment often occurs 1 to 2 years after program introduction, focusing on the 1997 to 2010 CREP cohorts helps mitigate concerns related to potential discontinuities in program funding following the initial enrollment wave.

Thus, my analysis focuses on (i) 250 counties where CREP was introduced between year 1997 and 2010 and (ii) 137 counties where CREP was not introduced until 2010. These counties are distributed across 13 states within two farm resource regions in the Mississippi River Basin: Heartland and Mississippi River Portal regions.[7] 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. Figure 1 presents a map that summarizes spatial and temporal variation in the timing of CREP introduction across counties included in the analysis.

[7] The list of 13 states includes Arkansas (AR), Illinois (IL), Indiana (IN), Iowa (IA), Kentucky (KY), Louisiana (LA), Minnesota (MN), Mississippi (MS), Missouri (MO), Nebraska (NE), Ohio (OH), South Dakota (SD), and Tennessee (TN). Farm resource regions are defined by the USDA 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.

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 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 significantly expands 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 introduction 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 value of variables used in the main analysis for counties where CREP was introduced between 1997 and 2010 and counties where CREP was not introduced until 2010.

4.1 Conservation Reserve Enhancement Program

The USDA-FSA provides county-by-year panel data on CREP introduction (a binary indicator) and participation (acres enrolled by practice type and total annual payments) from 1997 to 2022. CREP is introduced to a county when landowners can receive program payments for adopting conservation practices on agricultural land. A county is considered to participate in CREP once at least one landowner in the county enrolls a positive number of agricultural acres under a CREP contract to implement the required conservation practices. Thus, the first year of program introduction may differ from that of program participation, as landowners may not enroll any acres as soon as the program becomes available.

Figure 2 provides an overview of timing variation in the CREP introduction and participation across counties included in the analysis.[8] CREP introduction varies spatially and temporally even within the same state as the federal-state partnership on CREP may prioritize a specific watershed region to address environmental concerns and then subsequently expand the program to other

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

regions with similar or different environmental and resource concerns. For instance, in FY 2005, the Indiana State Department of Agriculture partnered with USDA-FSA and introduced CREP to counties in three watersheds to reduce agricultural nonpoint source pollution and restore wildlife habitat through the restoration of riparian buffers and wetlands. In FY 2011, Indiana expanded CREP to counties located in eight other watersheds in the state with similar environmental concerns. Out of the 387 counties in the analysis, CREP was introduced in 15 percent of them in 1997. Program availability expanded steadily thereafter, exceeding one-half of all counties by 2006 and reaching a maximum of 65 percent by 2010.

CREP participation also 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). Out of 250 counties with CREP, the share of counties with program enrolled acres increased from 14 percent in 1997 to 79 percent in 2010, reaching a maximum of 91 percent in 2022.

There are several caveats in interpreting the program data. First, the annual participation data report the total acres currently under contract as the sum of newly and previously enrolled acres, excluding acres from expired contracts. As a result, these data do not track cohorts of established conservation practices over time and may understate the stock of practices that remain on the landscape after contract expiration as documented in Bigelow et al. (2020). Second, the payment data include only annual rental payments, which constitute the primary expenditure, but exclude one-time cost-share payments for practice establishment and administrative costs. As a result, the reported program expenditures understate total program costs.

Figure 3 presents an overview of the total acreage enrolled in CREP by practice type and the total program payments in 250 counties with CREP by the number of years since program introduction. During the initial 11 years of the CREP implementation, the government invested a total of $604 million (in 2022$, CPI-adjusted) in establishing approximately 372,603 acres of conservation cover on agricultural land. 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) restoration of wildlife habitat.

Roughly 67 percent of total acres of conservation practices established through CREP are riparian buffers, wetlands, and filter strips. Likewise, the restoration of wildlife habitat via vegetative buffers and conservation cover along the water bodies also accounts for 17 percent of total enrolled acres. The remainder of the conservation practices installed includes native grass and tree plantings. According to the USDA-NRCS Conservation Practice Physical Effects and scientific literature, these 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).

4.2 Flood Damage on Cropland

The Cause of Loss data from USDA-RMA provide detailed information on county-by-month crop loss covered reported in the federal crop insurance program, categorized by crop type, cause of loss, and coverage level, from 1989 to 2022. As condition (5) suggests, I obtain (i) the total number of crop acres flooded and (ii) the extent of damage on flooded acres measured by the ratio of indemnity payouts for flooded crop loss (in 2022$, CPI-adjusted) to the total number of flooded crop acres. 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 chosen coverage level for eight major crops in the analysis region (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, under a 75 percent coverage level, a producer is responsible for the first 25 percent of the loss (the deductible), and indemnity payments begin only when realized losses exceed this threshold. Suppose a farmer insures 100 crop acres and 40 of those acres were damaged by flood. With 75 percent coverage, the deductible is 25 acres, so only the remaining 15 acres trigger an indemnity payment, and 15 acres and corresponding payments are recorded in the data. Thus, no indemnified crop acres in each year may indicate at least three possible scenarios: (a) the county did not experience any crop loss, (b) the county had no insured crop acres regardless of the actual crop loss, or (c) 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 smaller number of crop acres insured or adoption of lower coverage level compared to comparison group, overstating the program's benefits.

To address this concern, the empirical analysis focuses on counties that satisfy two criteria. First, using the USDA-RMA Summary of Business data, I identify counties with insured acreage for eight major crops prior to 1997, the first year CREP was introduced anywhere in the Mississippi River Basin. I then examine whether insured acreage and average coverage levels exhibit similar pre- and post-policy level and trend between CREP counties and the comparison group. Second, the analysis focuses on counties that had at least one acre of flood-induced indemnified crop loss prior to 1997. These criteria have implications for external validity: the estimated impacts apply to crop-producing regions with insurance adoption and indemnifiable flood risk. Among 709 counties within the two farm resource regions of interest, 387 counties satisfy these two criteria.

I find divergence in the trends of average flood damage on cropland between counties with and without CREP after the first program introduction in the entire region in 1997 (Figure 4 and Figure A2). Overall, flooded crop losses indemnified under the federal crop insurance program have increased over time, potentially reflecting both greater weather variability and rising crop insurance participation. Losses are particularly large in years associated with major flood events in the Mississippi River Basin (e.g., 2008, 2011, 2014, and 2019), whereas losses are small in drought years such as 2012. However, the observed divergence in flood damage cannot be interpreted as a causal effect of CREP because counties with and without CREP differ along several dimensions that may affect flood damage, including geographical characteristics, weather conditions, and crop insurance adoption. In addition, the staggered rollout of CREP may obscure its impact when comparing aggregate trends in calendar time. These concerns motivate the use of an event-study design and estimation of valid counterfactual flood damage for counties with CREP in the empirical analysis.

4.3 Weather Condition

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

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

The section outlines the empirical methodology employed to estimate the causal impact of CREP introduction on crop loss due to flooding. The primary estimand of interest is the average treatment effect on the treated (ATT), which measures the average impact of CREP *introduction* on flood-related crop losses in counties where CREP was introduced by 2010. 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. Finally, I describe the county-specific DID approach, which constructs a comparison group for CREP counties using the partially pooled synthetic control method of Ben-Michael et al. (2022), and the validity of identification assumptions. Although I do not detail the cohort-specific DID approach, I complement the analysis with the heterogeneity-robust event-study estimator of de Chaisemartin and D'Haultfoeuille (2024) to assess differential pre-trends and to demonstrate the robustness of the main findings.

5.1 Estimands of Interest

Consider a dataset of annual crop losses observed for $i = 1, \dots, N$ counties over $t = 1, \dots, T$ years, where the timing of CREP introduction varies across counties ($N = 387$ and $T = 34$). Let T_i denote the first year CREP becomes available in county i (i.e., the first year county i is "treated"), assuming $T_1 \leq T_2 \leq \cdots \leq T_N$ for simplicity. Let $j = 1, \dots, J$ denote the counties where CREP eventually becomes available by year T ($J = 250$). Then, each CREP county j has annual crop loss observed for up to L_j years before CREP introduction $\left(L_j = T_j - 1\right)$ and at least 11 years after

CREP introduction.[9] Let N_0 denote the number of counties where CREP was never introduced by year T ($N_0 = 137$), with $T_i = \infty$ indicating these counties are 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 let $Y_{it}(t_0)$ denote the potential crop loss in year t if the CREP first becomes available in year t_0 $(= 1, \dots, T, \infty)$. Under the assumption of no policy anticipation effects, $Y_{it}(t_0) = Y_{it}(\infty)$ for $t < t_0$, and under the stable unit treatment value assumption (SUTVA), the observed crop loss outcome follows $Y_{it} = \mathbb{1}\{t < T_i\}Y_{it}(\infty) + \mathbb{1}\{t \geq T_i\}Y_{it}(T_i)$. To assess changes in program effects over time, let event time $k \leq K$ denote the number of years relative to the first year of CREP introduction T_j (i.e., $k = t - T_j$ and $K = 10$). The observed trajectory of crop loss in county j treated in year T_j across event time k, relative to its average crop loss in the L_j pre-policy periods, is:

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

The county-specific program effect for each treated county j is then the divergence between the observed and counterfactual trajectories of crop loss in the post-policy period $k \geq 0$:

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

where $\tau_{jk} = 0$ for any $k < 0$, assuming no program anticipation and spillover effects. Note, however, that the counterfactual trajectory of post-policy crop loss, $\dot{Y}_{jT_j+k}(\infty)$ (i.e., the trend in crop loss that would have occurred had CREP not been introduced in year T_j), is not observable for the same county j.

Aggregating county-specific program effects across all treated counties at event time k yields the average effect of CREP introduction at event time k:

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

[9] The dataset spans the period 1989–2022. Within the 1997–2010 timing cohort analyzed in this paper, the earliest and latest years in which CREP first became available are 1997 and 2010, respectively. The maximum pre-policy period L_j among these counties is therefore 21 years (1989 to 2010). All counties in this timing cohort have at least 11 years of post-policy observations and up to 26 years, corresponding to 2010-2022 (11 years) and 1997-2022 (26 years), respectively.

Finally, the estimand of interest is the overall effect of CREP introduction on crop loss across all treated counties, averaged over the K post-policy periods, is:

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

5.2 Identification Strategy

In an ideal experiment to assess the flood-mitigation benefits of CREP using a DID approach, we would compare 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 exhibit identical trajectories of crop loss due to shared determinants, such as inherent flood risk and trends in weather conditions ($\tau_{jk} = 0, k < 0$). After the introduction of CREP in one county, any observed divergence in flooded crop losses between the two counties can be attributed to the program's effect ($\tau_{jk} \neq 0\,,\ k \geq 0$), providing insights into the loss mitigating benefits of CREP. In this experiment, the county without CREP serves as a credible comparison unit, representing the counterfactual scenario of what would have occurred in in the county with CREP in the absence of the program.

However, my identification strategy faces two main empirical challenges. First, the spatial and temporal variation in the introduction 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 CREP and potentially heterogeneous program effects across counties require careful selection of a comparison group to avoid bias in estimating the causal 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).

The identifying variation comes from the staggered introduction of CREP across counties. I consider two DID approaches: (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 introduction (Arkhangelsky et al., 2021; Ben-Michael et al., 2022). I implement the latter approach and establish a comparison group for each county with

CREP 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 estimate the CREP impact using the heterogeneity-robust event-study estimator proposed by de Chaisemartin & D'Haultfoeuille (2024), which yields similar findings.

Consider first the county-specific program effect across event time τ_{jk}. A suitable comparison unit would provide the trajectory of crop loss each county with CREP would have experienced in the absence of the program, $\dot{Y}_{jT_j+k}(\infty)$. Any single county or all counties without CREP may not necessarily be a valid comparison unit. Instead, I construct a synthetic control, which is a weighted combination of non-CREP counties with similar *trends* in crop loss during pre-policy periods. Then, the estimated average program effect across event time, $\widehat{ATT}_k$ is obtained by averaging the estimated county-specific program effects $\hat{\tau}_{jk}$. This 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; Ben-Michael et al., 2022; Sears et al., 2023).

5.3 Difference-in-Differences using Synthetic Control Method

To construct a comparison group for counties with CREP, I employ the partially pooled SCM proposed by Ben-Michael et al. (2022). This estimator takes the form of a weighted DID estimator that constructs a synthetic control county for each CREP county by allocating weights for counties without CREP (both never treated and not-yet treated[10]) to minimize two imbalance measures: (i) the *average difference* in pre-policy trends of flood damage between the CREP counties and synthetic control counties (individual fit) and (ii) the *difference in average* pre-policy trends of flood damage between the CREP and synthetic control counties (pooled fit). In Appendix B, I describe the weight allocation procedure in detail.

In addition to pre-policy trends in flooded crop loss, I include weather conditions 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

[10] For example, when estimating the initial 11 years of program effects for CREP counties in 1997, not-yet CREP counties include counties where CREP was introduced after 2010.

trends in crop loss. For example, crop profitability by crop type, land management, and farming practices are likely to be similar across counties that experience similar weather conditions in addition to similar experience in crop loss. Thus, synthetic control counties likely consist of qualitatively similar farms compared to the CREP counties, except for the introduction of CREP.

For each CREP county j, let $\gamma_{ij} \geq 0$ denote the synthetic control weight assigned to county i that CREP has never or not-yet been introduced for K years (i.e., $T_i > T_j + K$), where the weights are non-uniform, sparse, and sum to 1, $\sum_i \gamma_{ij} = 1$. Then, the county-specific program effect, $\hat{\tau}_{jk}$, across event time k is:

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

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

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). This estimator addresses bias arising from potential program effect heterogeneity and timing variation in program introduction. Key identification assumptions include the absence of time-varying confounding factors, policy anticipation effects, and spillover effects. For statistical inference, I use wild bootstrap to construct confidence intervals for the estimated ATT.[11]

Time-varying confounding factors would bias the estimated program effect because post-policy differences in crop loss between counties with CREP and those without CREP may be attributable to external factors rather than the program, such as crop insurance adoption, weather conditions, and investments from other conservation programs. For instance, a decrease in crop insurance adoption, either acreage insured or coverage level of loss, in CREP-available counties after the program introduction could decrease overall reported crop losses relative to non-CREP counties, 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. Conversely, reduced investments from other conservation programs that support similar practices

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

in CREP counties may lead to an underestimated CREP impact. Although the assumption of no time-varying confounding factors is fundamentally untestable, I examine whether key observed time-varying confounding factors exhibit parallel trends both *before* and *after* the CREP introduction to enhance the credibility of the estimated program effect (Section 6.2).

Suppose that conservation practices implemented through CREP effectively reduce flood-induced crop losses. Spillovers across counties could bias the estimated program effect: the estimate may be biased downward if CREP-induced mitigation in upstream counties reduces flood damage in downstream non-CREP counties used to construct synthetic controls, or biased upward if CREP-induced mitigation in upstream counties further reduces flood losses in downstream CREP counties. The assumption of no spillover effects is plausible if (i) the flood-mitigation benefits dissipate with distance and primarily accrue to cropland within the same farm, or (ii) the federal-state partnership's decision to introduce CREP in each county is not systematically correlated with the share of upstream CREP counties or with the magnitude of cross-county spillovers. I examine the robustness of the estimated program effect when neighboring non-CREP counties are excluded from the comparison group (Section 6.2).

CREP in the Mississippi River Basin mitigates concerns about reverse causality, as the program's initiation was unlikely to be influenced by county-specific trends in indemnity receipts for flood-related crop loss. Instead, the federal-state partnership's primary goal was to address broader environmental concerns that extend beyond local implementation areas, such as reducing agricultural nonpoint source pollution in the Gulf of Mexico and restoring wildlife habitat (Allen, 2005). While inherent flood risk in the region may contribute to fertilizer and pesticide runoff and influence the program's introduction for water quality improvement, time-invariant confounding factors are largely addressed by the DID approach.

The assumption of no policy anticipation effect is plausible for several reasons. First, landowners typically make long-term conservation decisions for their agricultural land, while tenant farmers handle operational decisions related to crop production and insurance. This distinction reduces concerns about potential anticipation effects on crop insurance and cropping decisions for rented farms.[12] Second, farmers have little incentive to manipulate flood-related crop loss in anticipation of CREP introduction. CREP payments are based on the average county-level

[12] 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).

soil rental rate, adjusted for site-specific soil type, and are not tied to crop types or yields. Third, CREP has stringent eligibility criteria for participation, including cropland location (proximity to streams or water bodies), a cropping history of four to six years using normal practices, and specific land characteristics that indicate potential environmental benefits. Given these factors, landowners are not likely to adjust cropping practices or manipulate reported losses in anticipation of program implementation. To assess the validity of these assumptions, I examine whether pre-policy trends in flood damage differ between counties with and without CREP (Section 6.2).

6. RESULTS

Section 6.1 first presents the spatial distribution of estimated weights $\hat{\gamma}_{ij}$ to show that synthetic controls for CREP counties are predominantly constructed from non-CREP counties within the same state or in neighboring states. I then discuss the estimated flood-mitigation effects of CREP over 11 years since program introduction (i.e., $\widehat{ATT}_{k=0,1,\ldots,10}$ and the overall $\widehat{ATT}$ in equations 9 and 10). Section 6.2 examines the credibility of key identification assumptions, including evaluations of parallel pre- and post-policy trends in observable confounding factors, pre-trend placebo tests, and estimation of program effects without bordering non-CREP counites. Section 6.3 reports two additional placebo tests. Section 6.4 decomposes the estimated flood-mitigation effects into the two mechanisms derived from the theoretical framework. Finally, Section 6.5 investigates spatial and temporal heterogeneity in the flood-mitigation benefits of CREP.

6.1 Flood-mitigation benefits of CREP Introduction

Consider first the extent of damage on flooded crop acres measured by the indemnity payout per flooded acre. 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 counties without CREP but located within the same state (67 percent) and a neighboring state South Dakota (16 percent) on average. Each synthetic control county typically consists of 5 to 12 different untreated counties with an average of 8 counties with a standard deviation of 2.4, excluding counties with assigned weight less than 0.001. Overall, the diagonal pattern in Figure 5 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 weather conditions.

Before the introduction of CREP, both counties with CREP and the synthetic control exhibited relatively 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 \$0.9/acre lower than those in the synthetic controls during the pre-policy periods, but the gap increases to \$26.2/acre during the post-policy periods (CREP: \$63.3/acre to \$75.5/acre; SC: \$64.2/acre to \$101.7/acre). Subtracting the pre-policy difference from the post-policy difference yields economically and statistically significant flood-mitigation benefits of conservation investments made through CREP (Figure 7).

During the first 11 years of program implementation, the estimated average reduction in annual indemnity payouts per acre loss is \$25.3/acre. This corresponds to a 25.1 percent decrease from the estimated counterfactual crop loss of \$100.8/acre, calculated as the average post-policy flood damage in synthetic control (\$101.7/acre) adjusted by the pre-policy difference in average outcome (-\$0.9/acre). The magnitude of flood-mitigation benefits generally increases with program duration: the average reduction is \$14.7/acre during the first 6 years and rises to \$38.1/acre during years 7 through 11. This temporal change in the benefits aligns with the trajectory of CREP enrollment after the program introduction (Figure 3).

I also find that the number of flooded crop acres reported for insurance claims in counties with CREP decreased after the program introduction. During the pre-policy periods, the average annual flooded crop acres in counties with CREP are only 26.8 acres fewer than those of the synthetic control counties during the pre-policy periods, while the difference increases to 218.2 acres during the post-policy periods (Figure A3) (CREP: 403.9 acres to 328.4 acres; SC: 430.7 acres to 546.6 acres). During the first 11 years of program implementation, the number of flooded crop acres decreases by 36.8 percent (191.4 acres; Figure A4) from the estimated counterfactual crop loss of 519.8 acres. The magnitude of reduction in the flooded crop acres also increases from 176.9 acres during the first 6 years to 208.8 acres during years 7 through 11.

To quantify the overall flood mitigation benefits generated by the introduction of CREP, I combine two components of avoided indemnity payouts: (a) reduced indemnity payouts per flooded acre, and (b) indemnity payouts avoided through the reduction in the number of flooded

acres. First, the program reduced the severity of damage on 328.4 flooded crop acres by $25.3 per acre during the post-policy period. Second, the program reduced the number of flooded crop acres by 191.4 acres (Figure A4), and each of these avoided flooded acres would have generated indemnity payouts of $100.8 per acre in the absence of the program (Figure 6). Combining these two components implies that the program lowered indemnity payouts by a total of $76 million during the initial 11 years of implementation across 250 CREP counties ($14 million to $131 million if using upper and lower bound estimates from the 95 percent confidence intervals). Given that the indemnity payout only covers a portion of flood damage, dividing the reduction in indemnity by the post-policy average of loss coverage level in counties with CREP (72.1 percent; Figure A7) yields $105 million reduction in flood-related crop losses.

To assess the cost-effectiveness of CREP in mitigating the flood damage, I compare the reduction in total indemnity payouts ($76 million) with the government's spending on CREP during the same period in CREP counties ($604 million). This implies that CREP generated financial spillover benefits to the federal crop insurance program of average $126 in avoided indemnity payouts per $1,000 of CREP spending ($24 to $217 if using upper and lower bound estimates from the 95 percent confidence intervals) or $174 in avoided crop loss per $1,000 of CREP spending ($33 to $301 if using upper and lower bound estimates from the 95 percent confidence intervals).

The magnitude of estimated flood-mitigation benefits relative to CREP payments (17.4 percent) likely represents a lower-bound estimate for two reasons. First, natural infrastructure established through PES programs may remain effective well beyond the initial contract period (Bigelow et al., 2020). Second, the flood-mitigation benefits of wetlands or floodplain conservation may extend beyond agricultural land and can also reduce damages to residential and other non-agricultural areas (Kousky & Walls, 2014; Taylor & Druckenmiller, 2022). At the same time, the estimated benefit-cost ratio may be overstated, because the program data exclude other program costs, including one-time cost-share payments for practice establishment 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 habitat, 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 Credibility of Identification Assumptions

The key identification assumption of weighted DID estimators is the absence of (i) time-varying confounding factors (ii) policy anticipation effect and (iii) policy spillover effect that bias the estimated impact of CREP introduction. In this section, I conduct a series of analyses to examine the credibility of each assumption.

First, although the assumption of no time-varying confounding factor is fundamentally untestable due to unobserved confounding factors, I examine the credibility assumption by investigating whether key observable time-varying confounding factors, such as crop insurance adoption, crop type, weather conditions, and conservation investments from other similar PES programs, have relatively parallel pre- and post-policy trends between counties with CREP and the synthetic control. First, I find that both the number of insured acres by crop type and the coverage level adopted have relatively parallel pre- and post-trend between counties with CREP and synthetic control group (Figure A5, A6, and A7).[13] Second, 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 (Figure A8 and A9). Third, I do not find significant divergence in post-policy trends of conservation investments made by 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

[13] The introduction of CREP and the adoption of conservation practices may not significantly influence insurance uptake for several reasons. First, the environmentally sensitive cropland eligible for CREP likely comprises only a small portion of the total insured acreage within a county. Second, the loss-mitigating benefits of conservation practices may be uncertain or not immediately evident to landowners, particularly in the short term. Third, the federal crop insurance program provides coverage against a broad range of agricultural income risks, including yield losses from other natural disasters and revenue declines due to market price fluctuations. These are risks that conservation practices may not directly address.

(previously Wetland Reserve Program), which conserves wetlands under long-term easement contracts (Figures A10 and A11). Overall, the post-policy reduction of flood damage in counties with CREP may not be driven by post-policy divergence in these key confounding factors.

Second, to assess potential policy anticipation effects, I estimate the impact of CREP on flood damage using the heterogeneity-robust event-study estimator proposed by de Chaisemartin and D'Haultfoeuille (2024). Unlike conventional two-way fixed-effects event-study regressions, which can yield biased estimates under staggered treatment timing and heterogeneous effects (Sun and Abraham, 2021), this estimator provides unbiased dynamic treatment effects and corresponding placebo pre-treatment effects. The placebo coefficients mirror the post-treatment estimators but shift the comparison window entirely to periods prior to CREP introduction, using as controls the counties where CREP was never introduced by 2010 and the not-yet-treated counties. Under the identifying assumptions of no anticipation and counterfactual parallel trends, these placebo coefficients should be statistically indistinguishable from zero. I include the same set of weather covariates to adjust for heterogeneity in weather conditions across counties.

Figure 8 reports the estimated pre- and post-policy effects. I fail to reject the joint null hypothesis that the pre-policy coefficients equal zero for horizons from 2 to 9 years before CREP introduction. The p-value for the joint nullity test ranges from 0.58 when testing the first three pre-policy coefficients, to 0.25 when testing the first five, and 0.12 when testing the first nine. The joint null hypothesis is finally rejected at the 5 percent significance level when the first ten pre-policy coefficients are included in the test. The average of estimated coefficients from 1 to 10 pre-policy periods is small in magnitude ($1.9/acre) relative to the post-policy impact. Overall, both the visual evidence and the statistical tests indicate no strong evidence of differential pre-trends or policy anticipation effects (similar findings for the number of crop acres flooded outcome in Figure A12). Note also that the main findings remain robust when implementing DID by the cohort of program introduction. The estimated average CREP impacts on flood damage are a reduction of $29.2 per flooded acre in indemnity payouts and a reduction of 311.5 flooded crop acres, both statistically significant. Thus, both the average of county-specific DID estimates based on synthetic controls and the weighted average of cohort-specific DIDs across event times yield qualitatively consistent findings: the introduction of CREP substantially mitigated flood damage on cropland.

Finally, spillover effects from CREP to neighboring counties without the program may bias the estimated program effect downward if those counties also experience flood-mitigation benefits.[14] To examine this possibility, I classify counties into three groups: (a) CREP counties, (b) non-CREP counties that border at least one CREP county ("exposed" counties), and (c) non-CREP counties that do not border any CREP county ("unexposed" counties). The main analysis compares CREP counties with all non-CREP counties (groups b and c combined; Figure 7), which could attenuate the estimated effects if exposed counties benefit indirectly from CREP. To assess the magnitude of this downward bias, I re-estimate the program impact using only the unexposed non-CREP counties (group c) as the comparison group. The estimated reductions in both the number of flooded crop acres and indemnity payouts per flooded acre remain robust compared to the main results, suggesting that potential spillover effects to neighboring non-CREP counties are unlikely to be significant in magnitude (Figures A13 and A14).

6.3 Placebo Tests

I implement an in-time placebo test within the SC-based DID framework by artificially shifting each county's actual CREP introduction year five years earlier. This approach preserves the cross-county variation in treatment timing but ensures that all placebo "treatment'' dates fall in years when CREP was not yet available. To guarantee a sufficiently long placebo window and adequate pre-policy periods for constructing synthetic controls, I restrict the analysis to counties whose true CREP introduction occurred between 2002 and 2010. I then reconstruct synthetic controls and re-estimate the program effects around these placebo event times. Because the placebo treatment never actually occurred, the estimated effects should be close to zero if the empirical design is not spuriously producing dynamic treatment effects.

In the absence of the in-time placebo shift, I find statistically significant flood-mitigation benefits of CREP for the 2002-2010 cohorts in both indemnity payouts per flooded acre and the number of flooded crop acres (Figures A15 and A17). Under the in-time placebo assignment, however, the estimated program effects shrink markedly toward zero. For the first five years of

[14] 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).

the placebo event window (event times 0 to 4), the average magnitude of estimated impact decreases from -$32.1 to $4.1 in indemnity payouts per flooded acre and from a reduction of 261.6 acres to 60.1 acres in flooded crop acres (Figure A16 and A18). Beyond the first five placebo event-time years, the estimated effects begin to diverge and mimic the pattern of the original post-policy estimates because placebo event times of five or greater overlap with calendar years in which CREP actually became available. Overall, I do not find strong evidence that the main findings are driven by spurious dynamic patterns.

In addition, I examine 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. Since 1997, the federal crop insurance program has compensated insured producers for revenue losses caused by declines in crop prices, based on futures market prices. Thus, indemnity payouts attributable to price declines serve as a placebo outcome that should remain unaffected by the introduction of CREP. Contrary to the post-policy divergence in insurance claims for flood damage between the two groups, I do not find post-policy divergence in those related to declines crop price (Figure A19 and A20). This finding suggests that the comparison between counties with CREP and the synthetic control reveal differences in indemnity payouts that are specifically related to the introduction of CREP and the establishment of natural infrastructure. In addition, this finding implies that the observed divergence in flooded crop loss between the two groups is unlikely to be driven by differences in loss reporting behavior or transaction costs associated with receiving indemnity payouts.

6.4 Decomposing the Flood-mitigation Benefits: Conversion and Protection Effects

Section 3.2 outlined two primary mechanisms through which the introduction of a PES program such as CREP can reduce flood damage on cropland: (i) the conversion effect, which arises when at-risk cropland is removed from production and placed under conservation cover, eliminating the insured exposure of those acres; and (ii) the protection effect, which reflects the reduction in flood damage on the remaining cropland due to the hydrological and erosion-control services generated by restored natural infrastructure such as riparian buffers and wetlands. The total $76 million reduction in indemnity payouts following CREP introduction captures the combined effect of these two mechanisms on the number of flooded acres and the severity of flood damage (see conditions 5 and 6).

The conversion effect represents the avoided flood insurance claims that would have been paid on crop acres enrolled in CREP had they remained in production. Because spatially explicit data linking crop insurance records with CREP contracts at a more disaggregated level than the county are unavailable, I proceed under three key assumptions. First, all indemnity payouts for flooding originate from crop acres located within floodplains. Second, cropland enrolled in CREP is located within floodplains, as the program targets cropland adjacent to rivers, streams, and other waterbodies to enhance downstream water quality and wildlife habitat. Third, cropland enrolled in CREP has similar expected indemnity payouts for flood-related losses as the average floodplain cropland (i.e., no selection in expected indemnity for flood damage conditional on being in the floodplain). Under these assumptions, the conversion effect of CREP enrollment can be approximated by the expected indemnity payouts for floodplain cropland.

I calculate the expected annual indemnity payouts for flooding that CREP counties would have incurred in the absence of the program, using synthetic control estimates adjusted for pre-policy differences. This yields an annual expected indemnity payout of $158,010 (Figure A21). I then overlay the USDA Cropland Data Layer (CDL) for the same eight major crops used in the analysis with the Federal Emergency Management Agency (FEMA)'s National Flood Hazard Layer (NFHL) to identify cropland within the floodplains.[15] The average cropland area within these floodplains in synthetic control counties is 20,676 acres. Dividing the total indemnity payouts by this area yields $7.6 per acre in annual flood indemnity for cropland located within floodplains as the conversion effect.

Next, consider the annual reduction in indemnity payouts per acre enrolled in CREP during the post-policy period. CREP counties enrolled a cumulative total of 372,602 crop acres during the first 11 years of program implementation. Dividing the total reduction in insurance indemnity ($76 million) by the total enrolled acreage yields a $204 reduction per enrolled acre, or equivalently $18.5 per acre per year. Given that this reduction reflects the combined impact of the conversion and protection effects, the conversion effect ($7.6 per acre annually) accounts for approximately 41 percent of the total reduction in annual indemnity payouts per enrolled acre, and the remaining 59 percent is attributable to the protection effect.

[15] I use the USDA CDL data to align crop types in the indemnity payout data with the corresponding crop acreage located within floodplains, drawing on the earliest available 2008 dataset. For the floodplain delineation, I use the FEMA's map of 1-percent-annual-chance flood zones (A, AE, V, and VE), commonly referred to as the 100-year floodplains.

This decomposition should be interpreted with caution, as it abstracts from potential differences in the expected flood damage between cropland enrolled in PES programs and other cropland. In practice, the magnitude of the conversion effect depends on the characteristics of the enrolled cropland, such as flood risk, productivity, and crop insurance decisions that jointly determine expected flooded crop loss and indemnity payouts. Both landowners' adverse selection behavior and the program's targeting criteria play central roles. If landowners tend to enroll highly productive land that face increasing flood risk, the avoided flood damage and indemnity payouts (conversion effect) will be substantial. In contrast, if the program primarily targets marginal cropland with low productivity or low-risk land, the conversion effect will be relatively small. The *relative* magnitude of the conversion and protection effects may not vary proportionally with changes in the conversion effect, as it also depends on the magnitude of the flood-protection services provided by the established conservation cover. If conservation cover is established on high-risk land and generates disproportionately stronger flood-protection spillovers to neighboring high-risk cropland, both conversion and protection effects may increase simultaneously.

6.5 Program Effect Heterogeneity

The flood-mitigation benefits of PES programs may vary substantially across space, time, and institutional settings. To investigate the program effect heterogeneity, I conduct a descriptive analysis that examines the linear relationship between the estimated flood-mitigation benefits of CREP and a set of county characteristics that could explain the magnitude of benefits from the theoretical framework. To be specific, I regress the estimated county-by-event-time program effects $\hat{\tau}_{jk}(0 \leq k \leq 10)$ in equation (11), on county-level measures of (i) program participation, (ii) inherent flood exposure, (iii) the presence of engineered flood-control infrastructure, and (iv) crop insurance adoption. These characteristics are potentially endogenous, and the results should therefore be interpreted as descriptive associations rather than causal effects. Table 2 reports the regression results, and Table A2 provides summary statistics of all variables used in the analysis.

I find that the magnitude of benefits increases with both the duration of CREP availability and the cumulative acreage enrolled in the program (Panel A of Table 2). Counties with longer exposure to CREP experience larger reductions in indemnity payouts per flooded acre, and those that enrolled more acreage exhibit substantially greater declines in both indemnity payouts and flooded cropland. These findings are consistent with the theoretical prediction that the flood-

mitigation benefits of PES program increase with the program participation extent. They also confirm that the estimated benefits are likely driven by the adoption of conservation practices on agricultural land under CREP.

The magnitude of flood-mitigation benefits is greater on average in counties with inherently high flood exposure (Panel B of Table 2). Counties located in the downstream portion of the Mississippi River Basin (the Mississippi River Portal region) experience substantially larger reductions in indemnity payouts per flooded acre and in flooded crop acreage compared with upstream counties in the Heartland region. Similarly, I also find counties with more crop acres in the floodplains also exhibit larger reductions in crop acres flooded following CREP introduction. These results align with the theoretical prediction that the flood-mitigation benefits of PES programs increase with both the probability of flood events and the potential severity of losses when such events occur.

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 pre-existing flood mitigation measures. To quantify the extent of engineered protection, I calculate the crop area protected by levee systems, by overlaying the map of levee protected area from U.S. Army Corps of Engineer's National Levee Database with cropland area from the USDA CDL data. I find that the loss mitigating benefits are greater in counties with little flood protection for crop acres by levees (Panel C of Table 2). This result implies potential interaction of protection services provided by natural "green" and engineered "gray" infrastructures in mitigating flood damages.

Finally, counties more heavily insured against production risk tend to exhibit larger reductions in crop insurance claims after CREP introduction (Panel D of Table 2), potentially for two reasons. First, counties facing higher inherent production risk are more likely to adopt higher levels of insurance. Second, because indemnities scale with coverage level, counties with higher average coverage experience larger financial gains when CREP reduces flood losses. Counties with higher coverage levels show greater reductions in both indemnity payouts per flooded acre and total flooded crop acres. Conditional on coverage level, however, counties with more insured acres exhibit larger reductions in flooded acreage but smaller reductions in indemnity payouts per flooded acre. The number of insured acres seems to reflect the overall scale of crop production in

this case rather than the intensity of insurance protection given the heavy insurance premium subsidy.

Overall, the heterogeneity analysis indicates that the introduction of PES programs would generate greater flood-mitigation benefits and savings in indemnity payout in counties with (i) substantial participation in the program, leading to widespread adoption of conservation practices; (ii) high inherent flood exposure in crop production, (iii) limited protection from engineered flood-control infrastructure such as levees, and (iv) high levels of crop insurance loss coverage.

7. CONCLUSION

Current global initiatives to address the impact of climate change 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 to show that the introduction of PES programs mitigates economic losses in agriculture caused by extreme weather events. The theoretical analysis showed how introducing PES program payments increases the adoption of 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 quasi-experimental variation in the timing of CREP introduction across counties and employed two heterogeneity-robust DID estimators to estimate the flood-mitigation benefits of CREP.

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 years since program introduction. Although CREP was initially motivated by objectives such as addressing agricultural nonpoint source water pollution and restoring wildlife habitat, it also

provides substantial climate change adaptation benefits by establishing 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 flood-mitigation benefits from PES programs, as well as the relative contributions of the conversion and protection effects, likely vary substantially across regions and policy contexts. Second, while I find limited evidence of inter-county spatial spillover effects, this does not rule out the possibility of spillover effects among farms within the same county or across farms located along county borders. Third, the indemnity payout data do not capture losses on uninsured cropland and minor crop damage that is not covered by the federal crop insurance, potentially understating the broader impacts of PES programs. Finally, the empirical analysis focused on a land-use conversion PES program implemented in regions characterized by intensive crop production and substantial flood risk, suggesting that the external validity of the findings should be carefully considered.

Despite these caveats and limitations, this study provides robust causal evidence that PES programs can mitigate economic losses in agriculture from increasing extreme weather events. The findings also indicate that PES programs generate financial spillover effects on existing agricultural risk management programs by reducing indemnity payouts for weather-related losses. Thus, future analyses of PES programs should account for the loss-mitigating benefits of the natural infrastructure they establish, in addition to their environmental benefits, to provide a more comprehensive basis for program design and evaluation. Overall, the study highlights the critical role of PES programs in facilitating nature-based solutions for climate change adaptation in agriculture.

8. TABLES AND FIGURES

Table 1. Descriptive Statistics of Variables in the Main Analysis

Time Period (Year)	1989-1996		1997-2022	
County: CREP introduction by 2010	Yes	No	Yes	No
Panel A. Conservation Reserve Enhancement Program		Mean		
Number of acres enrolled	N/A	N/A	942.9	N/A
Annual program payments ($1,000s)	N/A	N/A	201.2	N/A
Panel B. Flood Damage on Cropland				
Indemnity payout due to flood ($1,000s)	53.8	85.3	77.3	207.4
Acres loss due to flood (acre)	399.2	538.4	332.1	713.0
Indemnity per flooded crop acre ($/acre)	62.2	64.5	78.9	104.1
Panel C. Federal Crop Insurance Program Participation				
Crop acres insured (1,000s)	103.6	85.4	184.6	161.6
Crop type: corn and soybean share of insured	0.91	0.88	0.94	0.91
Coverage level insured (%, area-weighted)	65.0	64.7	73.3	70.6
Panel D. Weather Conditions				
Total Precipitation (mm)				
Post-harvest (Oct-Mar)	353.0	422.2	361.8	422.4
Growing season (Apr-Sept)	644.7	663.6	612.3	627.9
Growing degree days (10-29 Celsius)				
Post-harvest (Oct-Mar)	201.1	255.5	223.6	278.7
Growing season (Apr-Sept)	1646.6	1781.1	1739.9	1871.9
Number of counties	250	137	250	137
Number of observations (county-by-year)	2,000	1,096	6,500	3,562

Notes: The table presents average values of listed variables for 250 counties where CREP was introduced and 137 counties where it was not by 2010. All monetary values are in 2022 USD.

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

Table 2. Program Effect Heterogeneity

Outcome: estimated program effect $\hat{\tau}_{jk}, 0 \leq k \leq 10$	Indemnity per crop acre flooded	Crop acres flooded
Panel A. Conservation Reserve Enhancement Program		
Duration of program availability in years	-2.18* (0.88)	17.9 (9.42)
Number of acres enrolled, standardized	-8.89** (3.01)	-60.3* (27.6)
Panel B. Inherent Flood Risk		
Downstream Mississippi River, binary indicator	-153.6*** (22.5)	-1827.7*** (339.7)
Crop acres within floodplain, standardized	-4.78 (3.22)	-103.0* (40.8)
Panel C. Alternative Flood Mitigation Measure		
Crop acres protected by levees, standardized	14.8*** (4.39)	126.3* (53.8)
Panel D. Federal Crop Insurance Program		
Coverage level insured, standardized	-15.0*** (3.40)	-126.2** (43.1)
Crop acres insured, standardized	7.08* (3.14)	-64.0* (31.8)
Constant	-2.96 (5.35)	-159.7*** (43.9)
Outcome mean	-25.3	-191.4
Weather control	Y	Y
Number of observations	2750	2750
Adj. R-squared	0.050	0.065
F-statistics	14.5	12.2

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<.001, ** p<.01, * p<.05

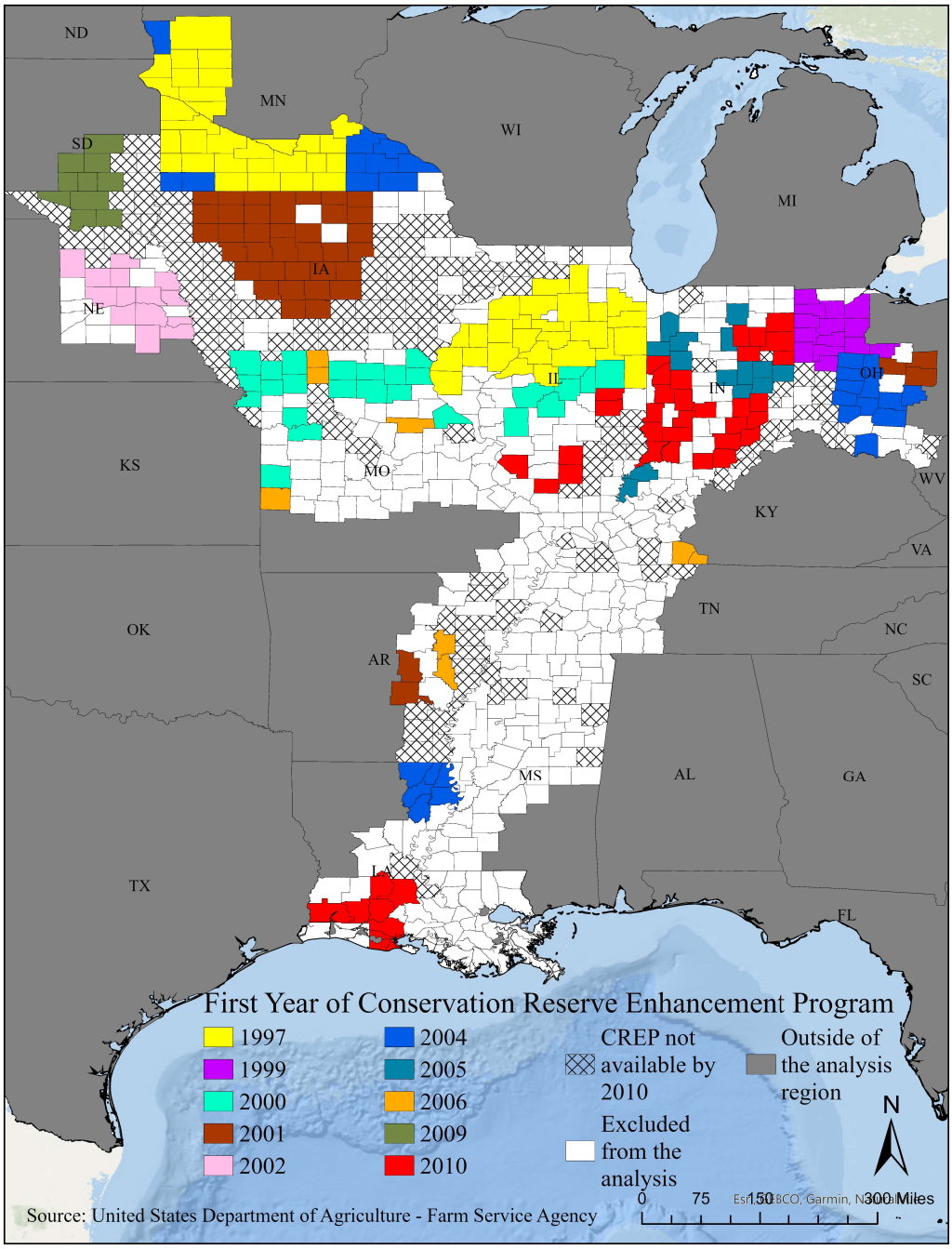
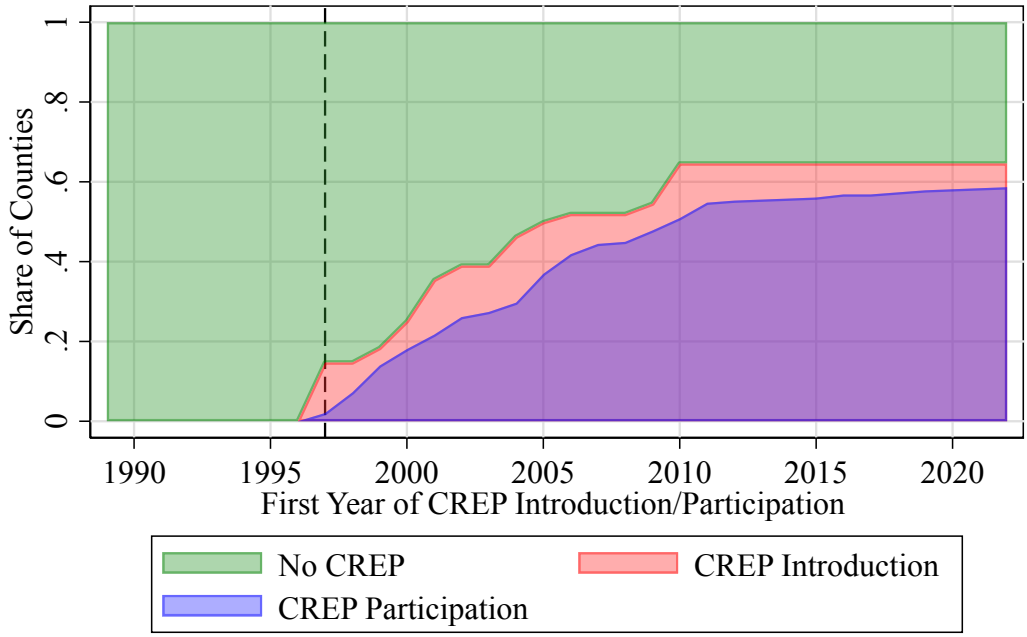


Figure 1. Spatial and Temporal Variation in the Introduction of CREP: Heartland and Mississippi River Portal Regions

Notes: The figure shows a map of counties in the analysis with spatial and temporal variation in the year (fiscal year-1) of Conservation Reserve Enhancement Program's introduction across counties. Out of a total of 709 counties in the Heartland and Mississippi River Portal regions, the analysis includes 387 counties that had any insured crop acres from 1989 to 1996 (1 year before the first year of CREP introduction). There are 250 counties that have introduced CREP and 137 counties that never introduced CREP by 2010.
Source: USDA Farm Service Agency



CREP Introduction: 250 counties from 11 states
CREP Participation: 227 counties from 11 states
No CREP: 137 counties from 12 states

Figure 2. Conservation Reserve Enhancement Program: Timing Variation of Introduction and Participation across Counties, 1997-2022

Notes: The graph shows the number of counties that introduced Conservation Reserve Enhancement Program (CREP) in any year before 2022 (y-axis) by the initial year of CREP introduction (red) or participation (blue) (x-axis). Among 387 counties included in the analysis, CREP has been ever introduced to 250 counties at different timings between 1997 and 2010. By the year 2022, 227 of these counties had enrolled crop acres in the program to establish conservation practice (program participation).
Source: USDA Farm Service Agency.

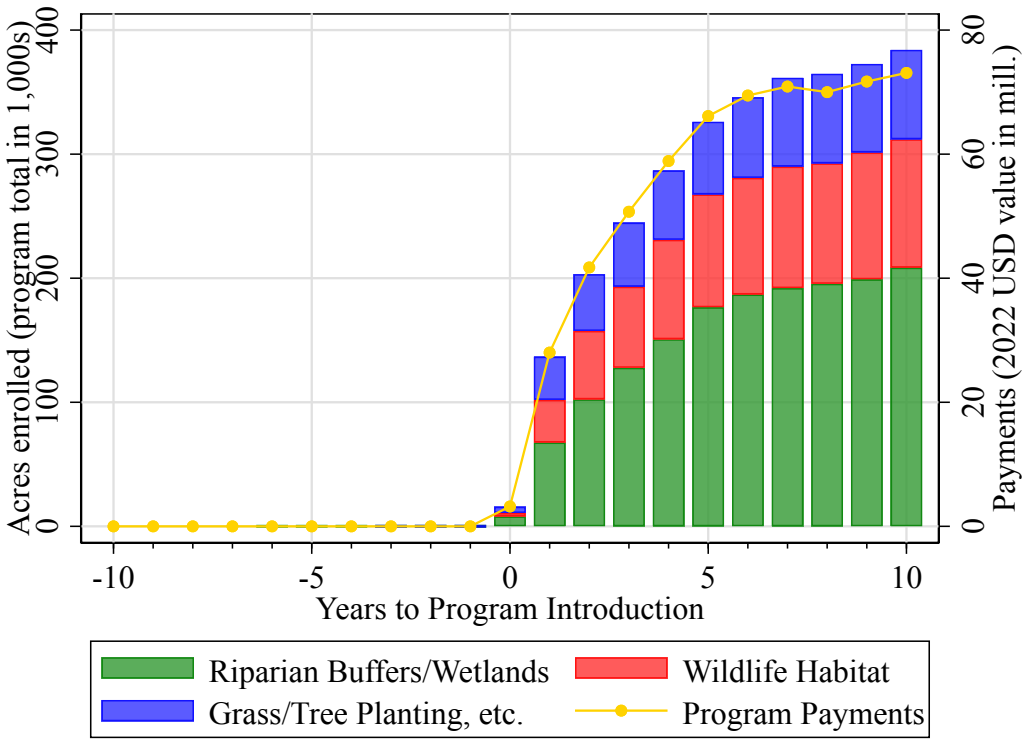


Figure 3. Conservation Reserve Enhancement Program: Enrolled Acres and Payments

Notes: The graph shows the total number of acres enrolled in the Conservation Reserve Enhancement Program (CREP) (left y-axis) and the corresponding payments made (right y-axis, in millions of 2022 USD value) for 250 counties in the analysis where CREP was ever introduced by 2010. The x-axis reports the number of years since the program introduction.
Source: Author's calculation using data from USDA Farm Service Agency.

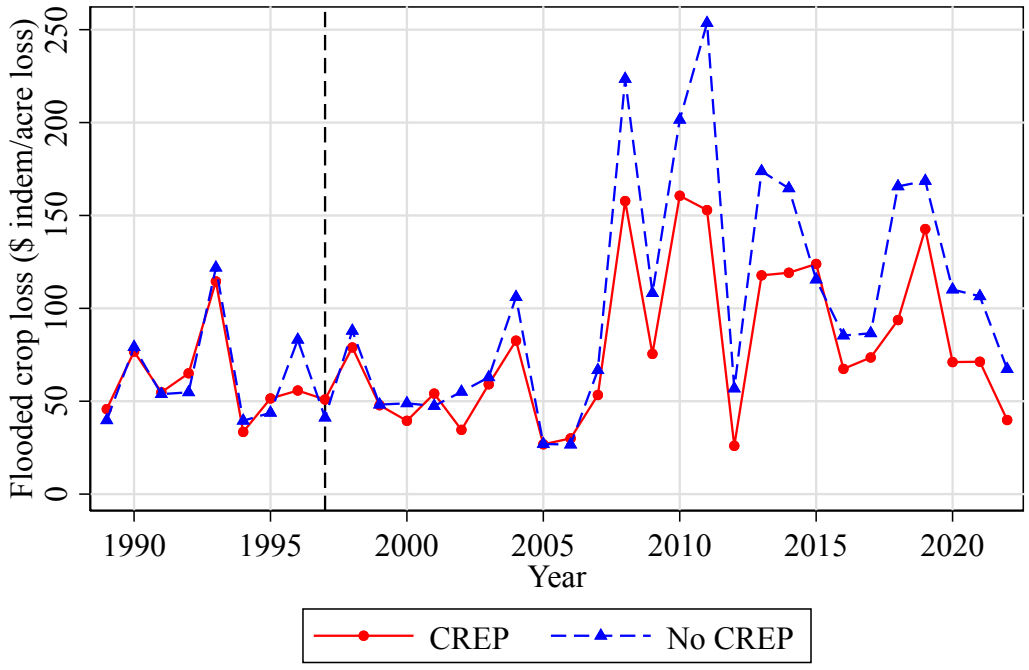


Figure 4. Trends in Indemnity payouts per Flooded Acres during 1997-2022 for Counties with and without Conservation Reserve Enhancement Program

Notes: The graph shows trends in the average indemnity payouts (in 2022 USD value) 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: Author's calculation using data from USDA Risk Management Agency and Farm Service Agency.

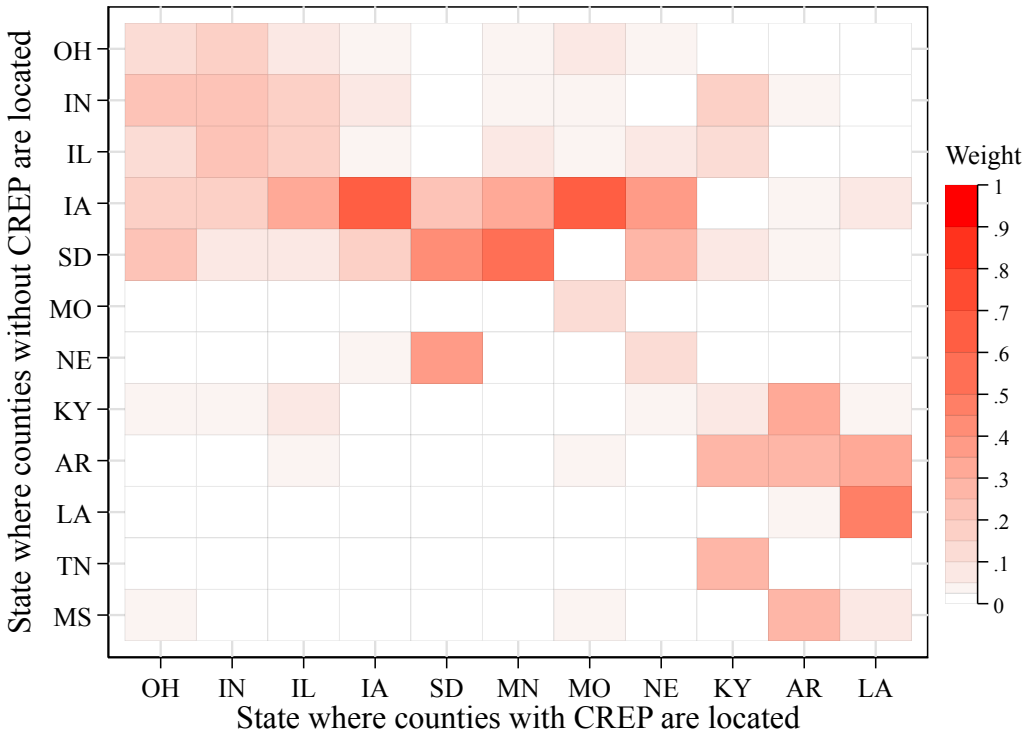
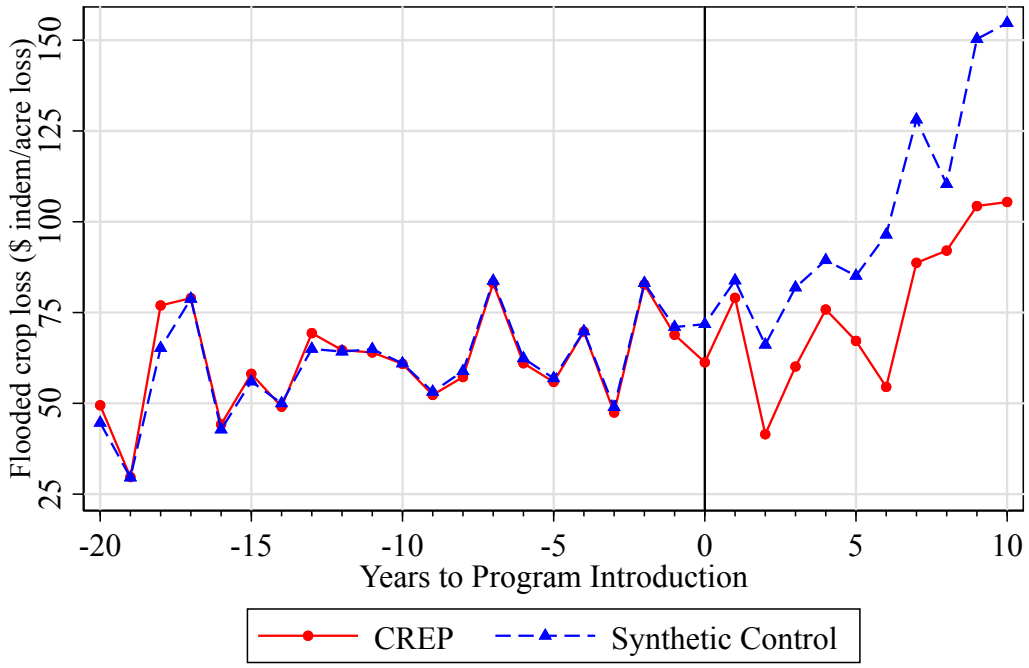


Figure 5. Spatial Distribution of Synthetic Control Weights allocated to Counties without CREP

Notes: The figure presents the average weights assigned to 137 counties without Conservation Reserve Enhancement Program (CREP) in each state (y-axis) when constructing synthetic controls for 250 counties with CREP in each 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 CREP counties (x-axis) and state b without CREP counties (y-axis).
Source: Author's calculation



Pre-policy avg.: CREP 63.3, Synthetic control 64.2, Pre-policy diff. = -0.9
Post-policy avg.: CREP 75.5, Synthetic control 101.7, Post-policy diff. = -26.2

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 USD value) (y-axis) in 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls by the number of years to the program introduction (x-axis).
Source: Author's calculation

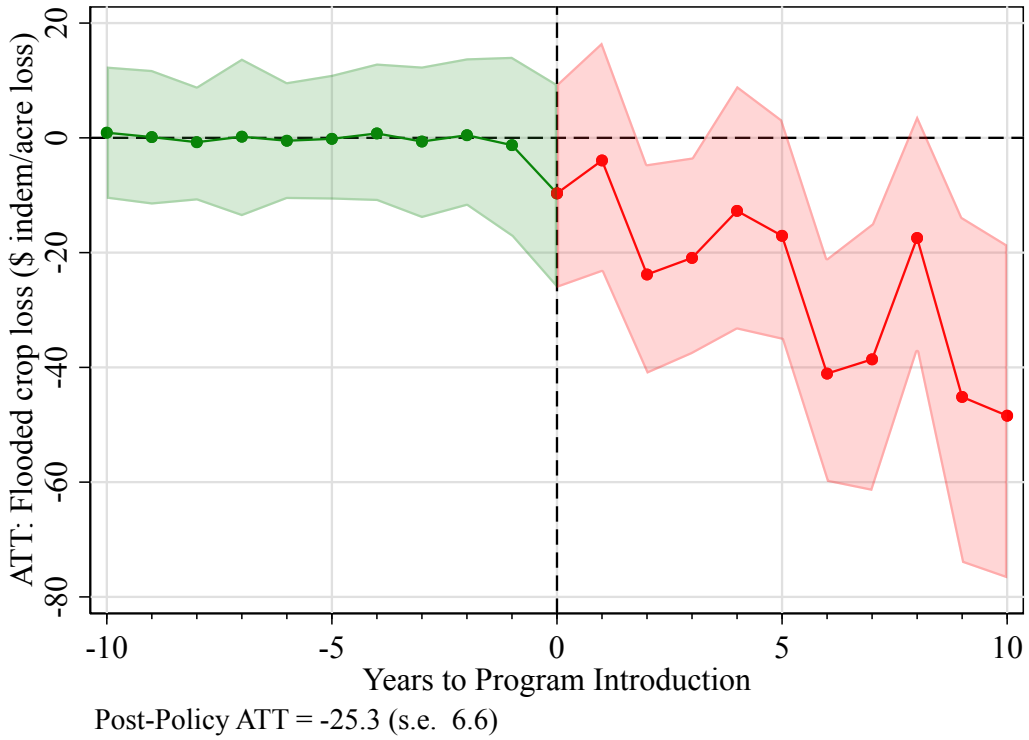


Figure 7. Estimated Impact of CREP Introduction on Flooded Crop Loss (DID with SC)

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 USD value, y-axis) across the number of years to the program introduction (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, flooded crop acres, 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 counties without CREP to construct synthetic controls. Confidence intervals (95%) are constructed using wild bootstrap.
Source: Author's calculation

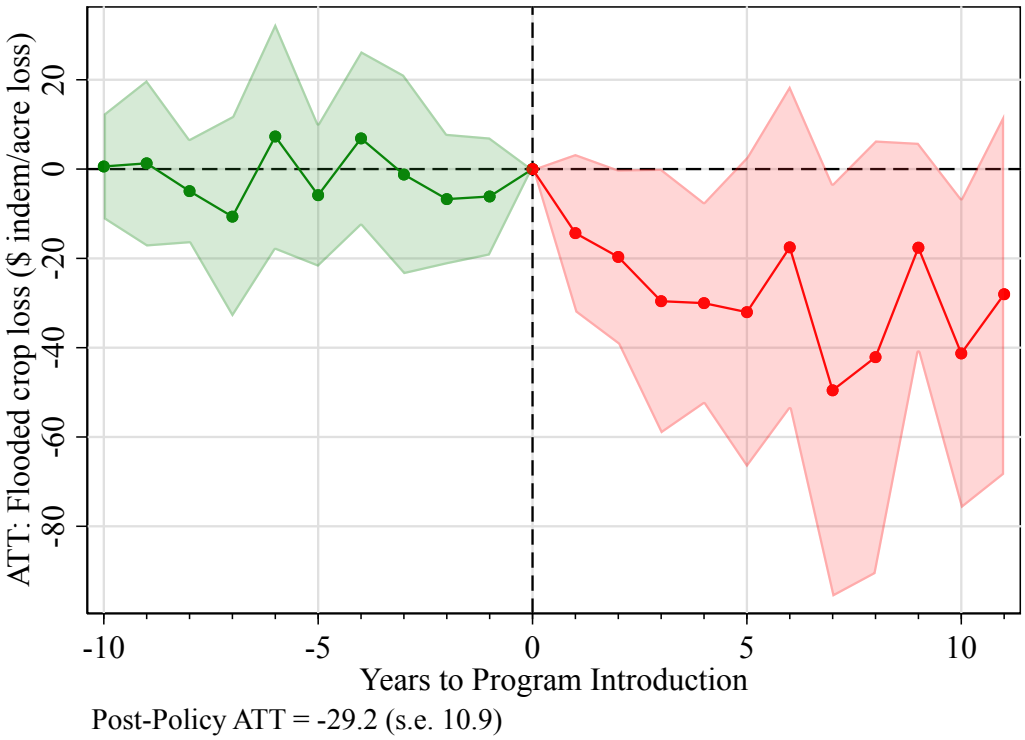


Figure 8. Estimated Impact of CREP Introduction on Flooded Crop Loss (Event Study)

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 USD value, y-axis) across the number of years to the program introduction (x-axis) with 95 percent confidence intervals. The average program effect is estimated with weather covariates using heterogeneity-robust event-study estimators proposed by de Chaisemartin and D'Haultfoeuille (2024). Weather covariates include precipitation (mm) and growing degree days during the post-harvest (October to March) and crop growing seasons (April to September).

APPENDIX A. SUPPLEMENTARY TABLES AND FIGURES

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

	Number of Counties				First Year of Program Introduction/Participation	
State	Total	Introduction	Participation	Not Available	Introduction (min, max)	Participation (min, max)
IL	55	40	37	15	(1997, 2010)	(1997, 2011)
MN	40	40	40	0	(1997, 2004)	(1998, 2007)
OH	37	29	28	8	(1999, 2004)	(1999, 2005)
MO	33	23	18	10	(2000, 2006)	(2001, 2007)
AR	18	4	3	14	(2001, 2006)	(2001, 2007)
IA	84	35	31	49	(2001, 2001)	(2002, 2022)
NE	18	14	13	4	(2002, 2002)	(2002, 2003)
LA	14	12	6	2	(2004, 2010)	(2005, 2005)
IN	52	41	39	11	(2005, 2010)	(2005, 2021)
KY	8	2	2	6	(2006, 2006)	(2006, 2007)
SD	19	10	10	9	(2009, 2009)	(2009, 2011)
MS	6	0	0	6	N/A	N/A
TN	3	0	0	3	N/A	N/A
	387	250	227	137		

Notes: The table reports the number of counties with CREP introduction and participation, as well as counties never offered the program by 2010, across 13 states in the Heartland and Mississippi River Portal regions. It also reports the first year of CREP introduction and any enrollment.
Source: USDA Farm Service Agency

Table A2. Descriptive Statistics: Heterogeneity Analysis

Variable Description	Mean	SD
Estimated Program Effect, county-by-post event time $\left(\hat{\tau}_{jk}, 0 \leq k \leq 10\right)$		
Indemnity payouts per flooded crop acre	-25.3	119.9
Number of crop acres flooded	-191.4	1303.6
Conservation Reserve Enhancement Program (CREP)		
Duration of CREP availability in years	5.0	3.2
Acreage enrolled	1064.5	2269.3
Inherent Flood Risk		
Downstream Mississippi River	0.1	0.2
Number of crop acres within floodplain (acre, 1,000s)	19.3	20.1
Alternative Flood Mitigation Measure		
Number of crop acres within levee-protected area (acre, 1,000s)	9.8	40.1
Federal Crop Insurance Program Participation		
Coverage level insured (%, area-weighted)	72.1	6.6
Crop acres insured (1,000s)	180.9	90.2
Weather (crop growing season)		
Total precipitation (mm)	624.1	152.4
Total growing degree days (10-29 Celsius)	1736.3	306.3
Number of observations (CREP county-by-post policy event time): 2,750		

Notes: The table presents summary statistics of variables used in the analysis of program effect heterogeneity for 250 counties that introduced CREP by 2011.
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).

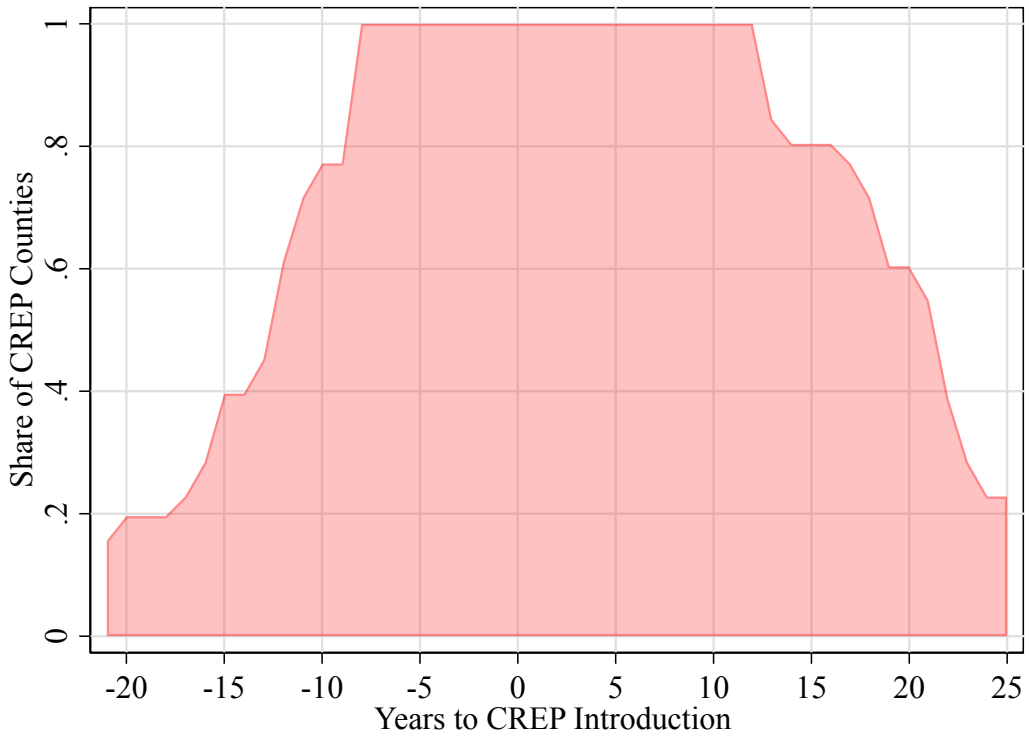


Figure A1. Share of CREP Counties by Years to Program Introduction

Notes: The figure shows the share of the 250 counties in which Conservation Reserve Enhancement Program (CREP) was introduced by 2010 across years to program introduction. Because the timing of CREP introduction varies across counties, a balanced panel in calendar years becomes an unbalanced panel when re-indexed by event time.
Source: Author's calculation using data from the USDA Risk Management Agency and Farm Service Agency.

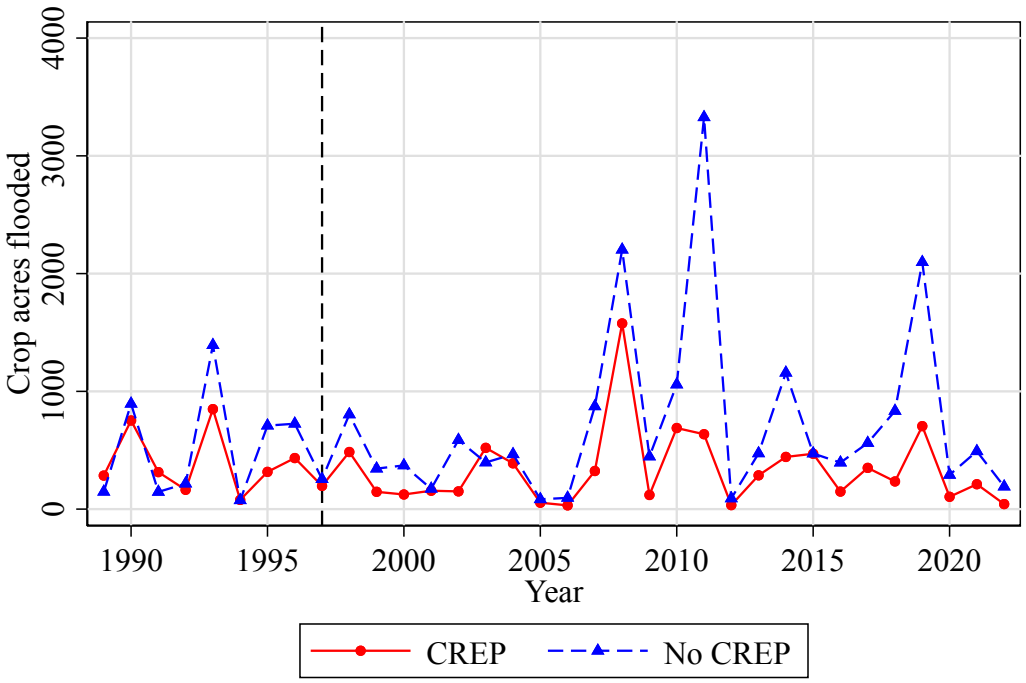
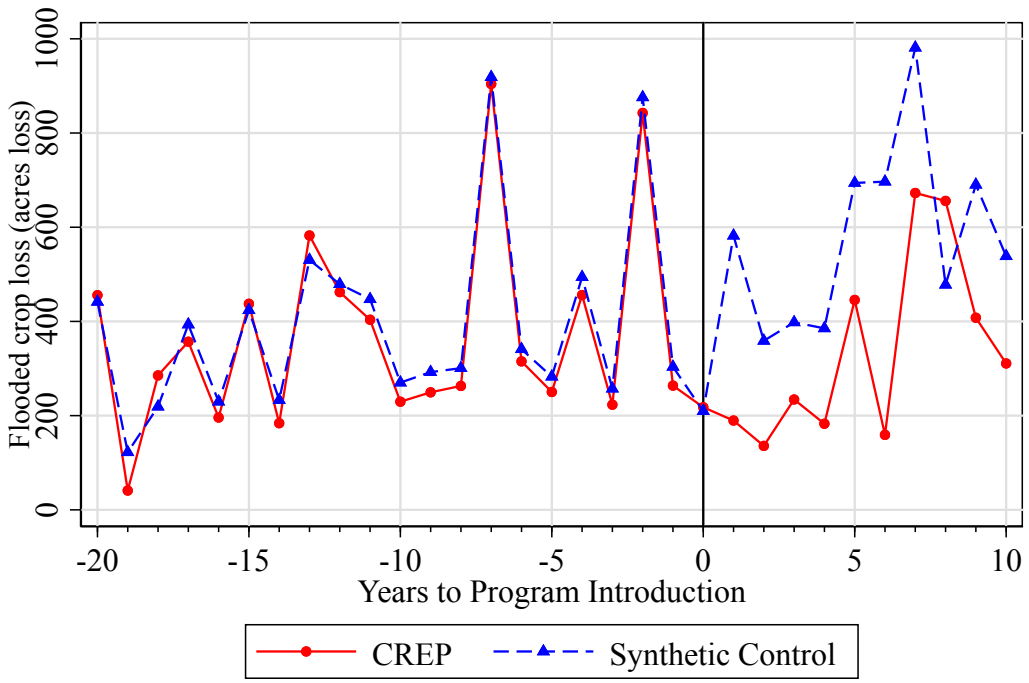


Figure A2. Trends in Crop Acres Flooded during 1997-2022 for Counties with and without Conservation Reserve Enhancement Program

Notes: The graph shows trends in the average flooded crop acres reported for insurance claims at the county level (y-axis), comparing counties with and without Conservation Reserve Enhancement Program (CREP) during years 1989-2022 (x-axis).
Source: Author's calculation using data from the USDA Risk Management Agency and Farm Service Agency.



Pre-policy avg.: CREP 403.9, Synthetic control 430.7, Pre-policy diff. = -26.8
Post-policy avg.: CREP 328.4, Synthetic control 546.6, Post-policy diff. = -218.2

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 the number of years to the program introduction (x-axis) in counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of counties without CREP.
Source: Author's calculation

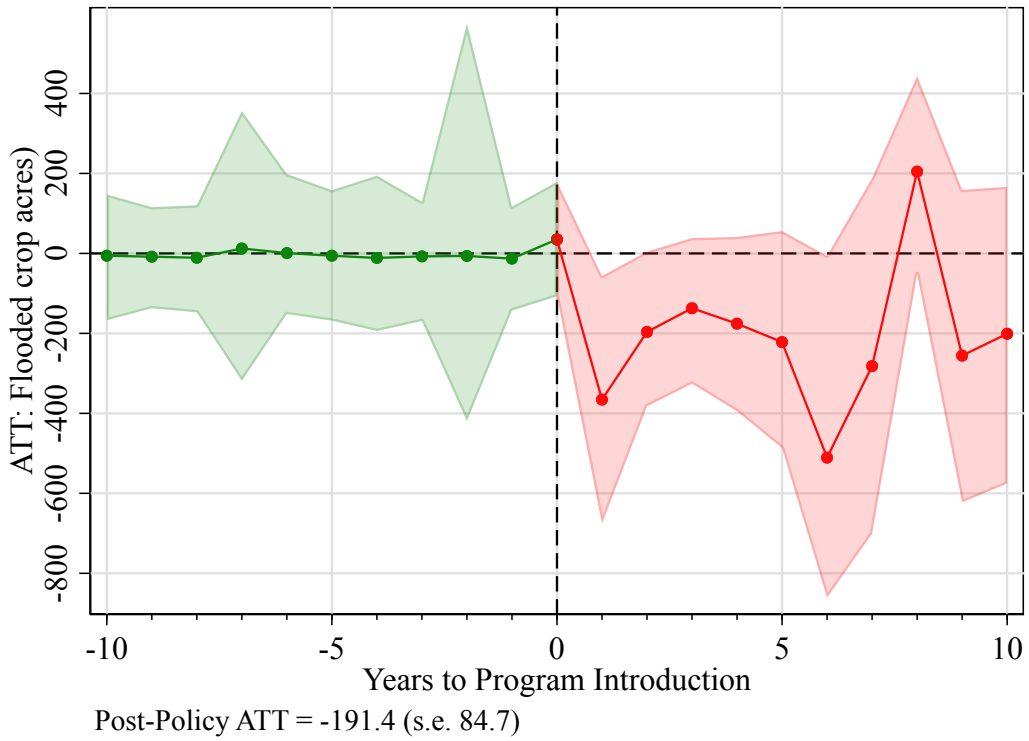
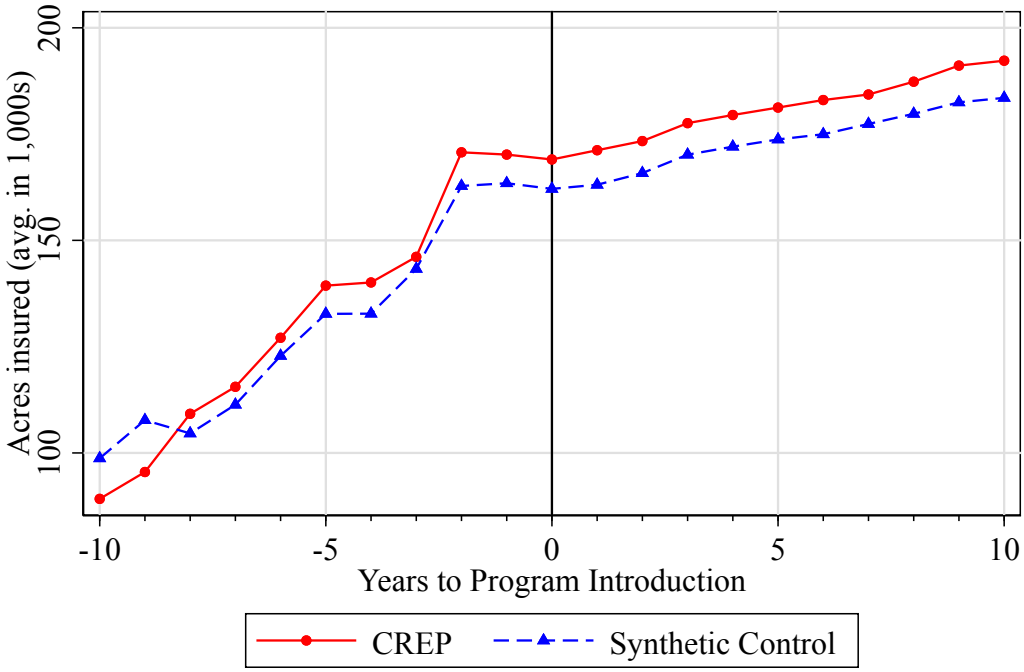


Figure A4. Estimated Impact of CREP Introduction on Crop Acres Flooded

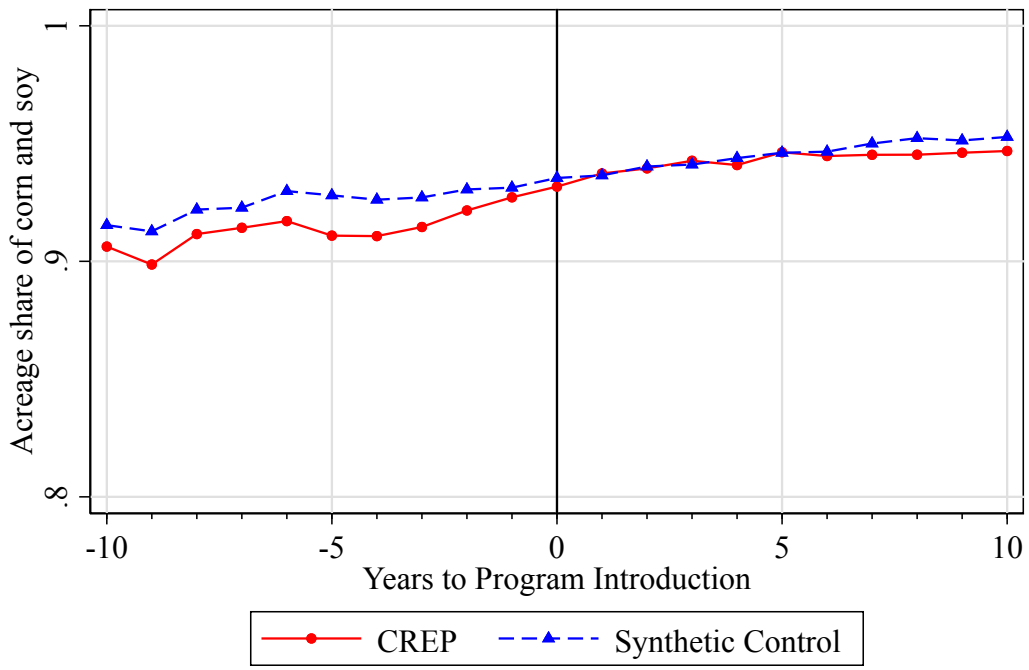
Notes: The graph shows the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop acres (y-axis) across the number of years to the program introduction (x-axis) with 95 percent confidence intervals. The estimated average program effect is calculated by comparing the average change in crop loss relative to pre-policy average between 250 counties with CREP and their synthetic controls. In addition to lagged flooded crop acres, indemnity payouts per acre loss, 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 counties without CREP to construct synthetic controls. Confidence intervals (95%) are constructed using wild bootstrap.
Source: Author's calculation



Pre-policy avg.: CREP 132.1, Synthetic control 129.2, Pre-policy diff. = 2.9
Post-policy avg.: CREP 180.9, Synthetic control 173.2, Post-policy diff. = 7.7

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

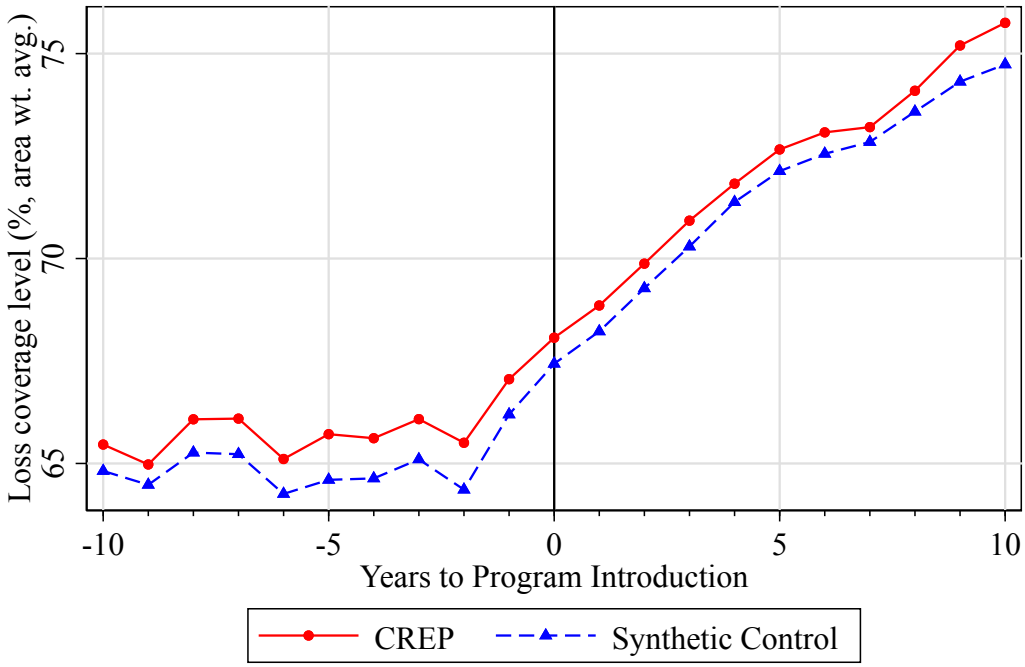
Notes: The graph shows trends in county-level average insured acres (y-axis) by the number of years to the program introduction (x-axis) in 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of counties without CREP.
Source: Author's calculation



Pre-policy avg.: CREP .91, Synthetic control .93, Pre-policy diff. = -.02
Post-policy avg.: CREP .94, Synthetic control .95, Post-policy diff. = -.01

Figure A6. Trends in Share of Acres Insured for Corn and Soybeans under the Federal Crop Insurance Program: Counties with CREP and Synthetic Controls

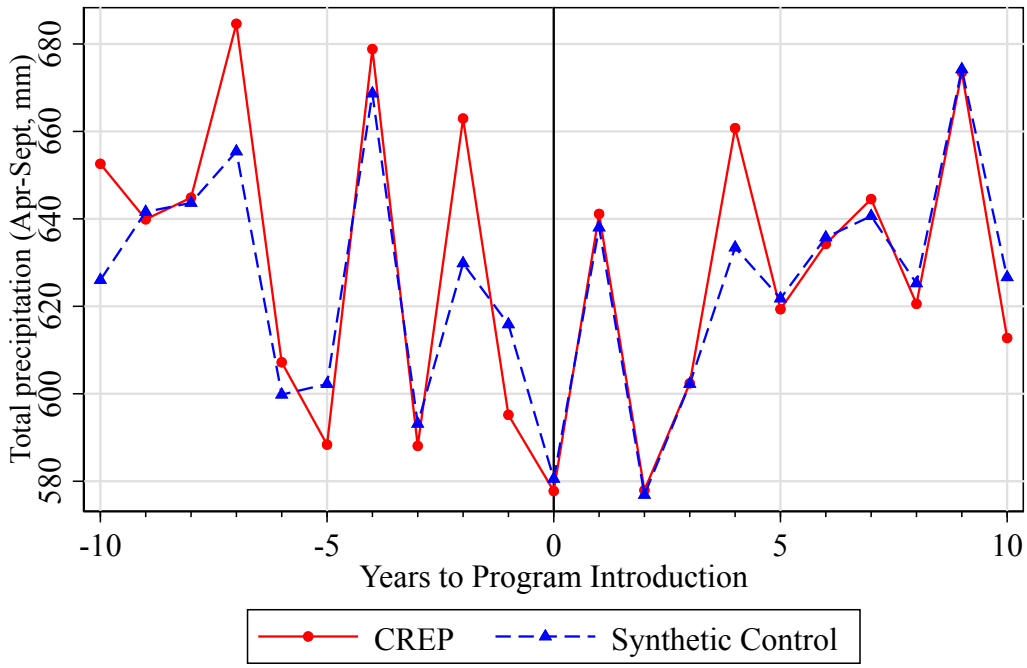
Notes: The graph shows trends in county-level average insured acres for corn and soybeans (y-axis) by the number of years to the program introduction (x-axis) in 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of counties without CREP.
Source: Author's calculation



Pre-policy avg.: CREP 65.8, Synthetic control 64.9, Pre-policy diff. = 0.9
Post-policy avg.: CREP 72.1, Synthetic control 71.5, Post-policy diff. = 0.6

Figure A7. Trends in Insurance Coverage Level under the Federal Crop Insurance Program: Counties with CREP and Synthetic Controls

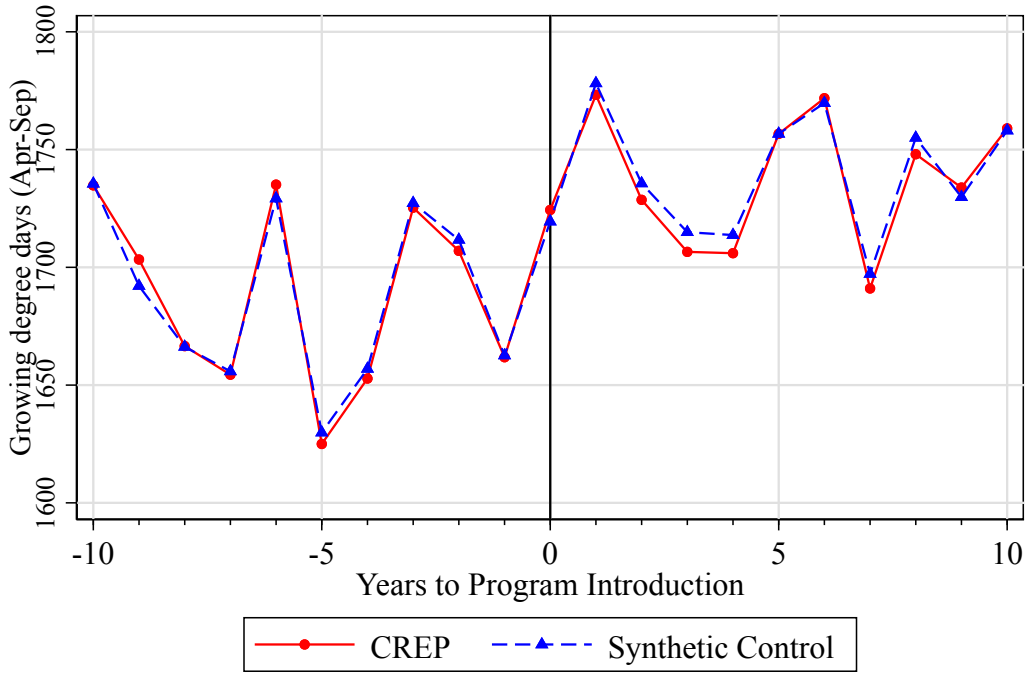
Notes: The graph shows how the coverage level for acres insured under the federal crop insurance program has changed by the number of years to the program introduction (x-axis) for both 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on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



Pre-policy avg.: CREP 633.7, Synthetic control 627.3, Pre-policy diff. = 6.4
Post-policy avg.: CREP 624.1, Synthetic control 623.2, Post-policy diff. = 0.9

Figure A8. Trends in Precipitation during Crop Growing Season: Counties with CREP and Synthetic Controls

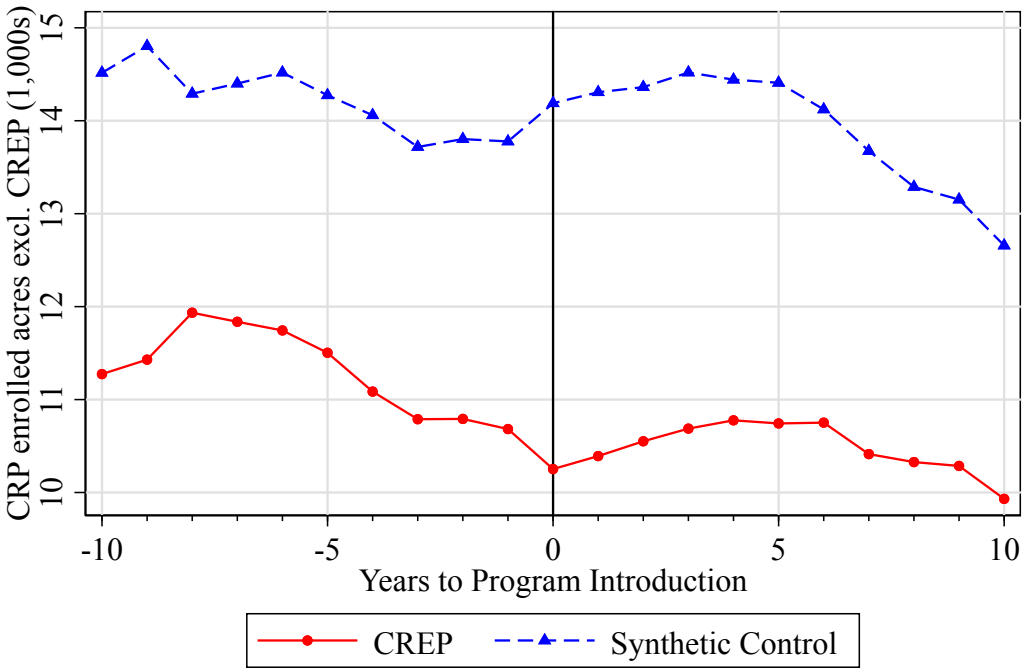
Notes: The graph shows trends in county-level average total precipitation (mm) during the crop growing season (April-September) (y-axis) by the number of years to the program introduction (x-axis) for both 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of counties without CREP.
Source: Author's calculation



Pre-policy avg.: CREP 1685.1, Synthetic control 1685.4, Pre-policy diff. = -0.3
Post-policy avg.: CREP 1736.3, Synthetic control 1738.9, Post-policy diff. = -2.6

Figure A9. Trends in Growing Degree Days (10-29 Celsius) during Crop Growing Season: Counties with CREP and Synthetic Controls

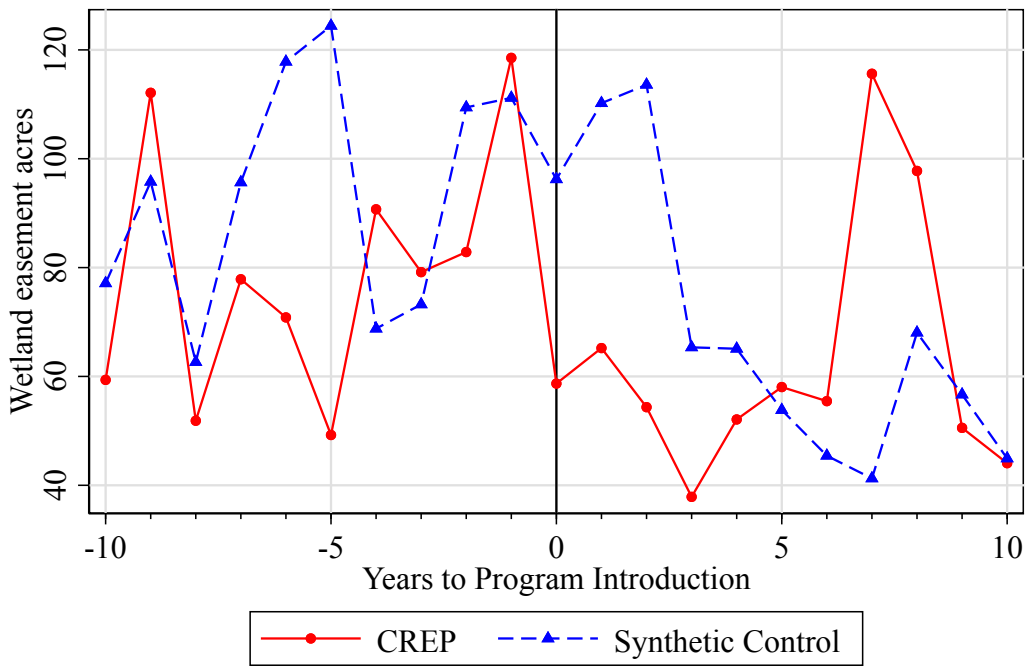
Notes: The graph shows trends in county-level average growing degree days during the crop growing season (April-September) (y-axis) by the number of years to the program introduction (x-axis) for both 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of counties without CREP.
Source: Author's calculation



Pre-policy avg.: CREP 11.3, Synthetic control 14.2, Pre-policy diff. = -2.9
Post-policy avg.: CREP 10.5, Synthetic control 13.9, Post-policy diff. = -3.4

Figure A10. 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 the number of years to the program introduction (x-axis) for both 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of counties without CREP.
Source: Author's calculation



Pre-policy avg.: CREP 78.9, Synthetic control 94, Pre-policy diff. = -15.1
Post-policy avg.: CREP 62.7, Synthetic control 69.2, Post-policy diff. = -6.5

Figure A11. 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 the number of years to the program introduction (x-axis) for both 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of counties without CREP.
Source: Author's calculation

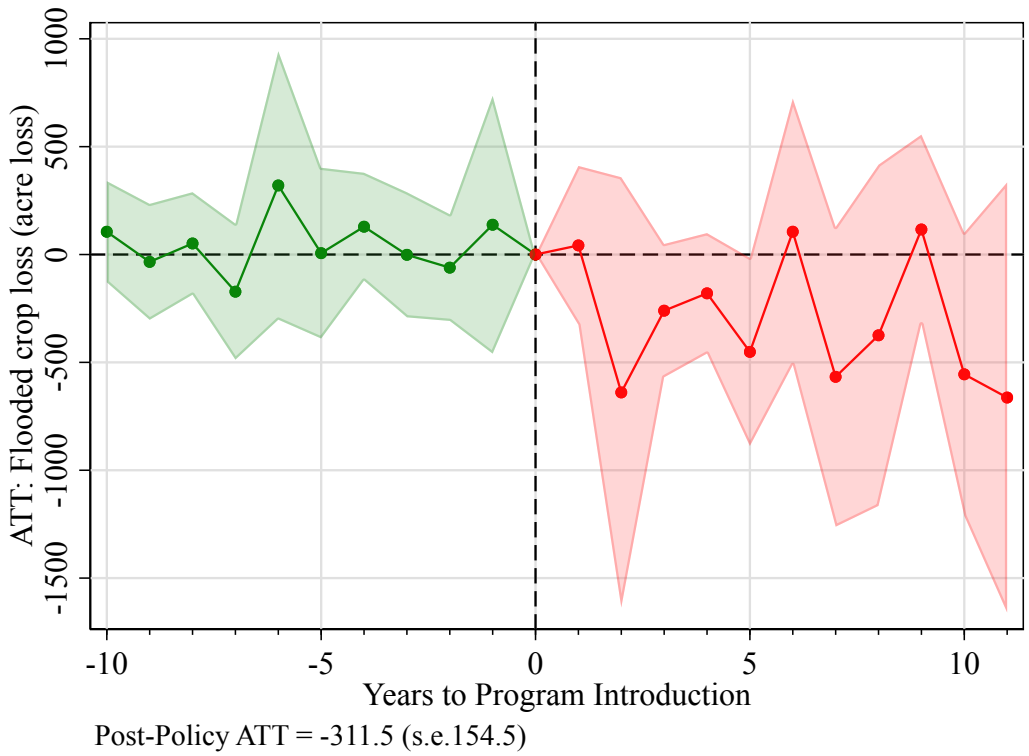


Figure A12. Estimated Impact of CREP Introduction on Crop Acres Flooded (Event Study)

Notes: The graph shows the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop acres (y-axis) across the number of years to the program introduction (x-axis) with 95 percent confidence intervals. The average program effect is estimated using the heterogeneity-robust event-study estimator proposed by de Chaisemartin and D'Haultfoeuille (2024). Weather covariates include precipitation (mm) and growing degree days during the post-harvest (October to March) and crop growing seasons (April to September).

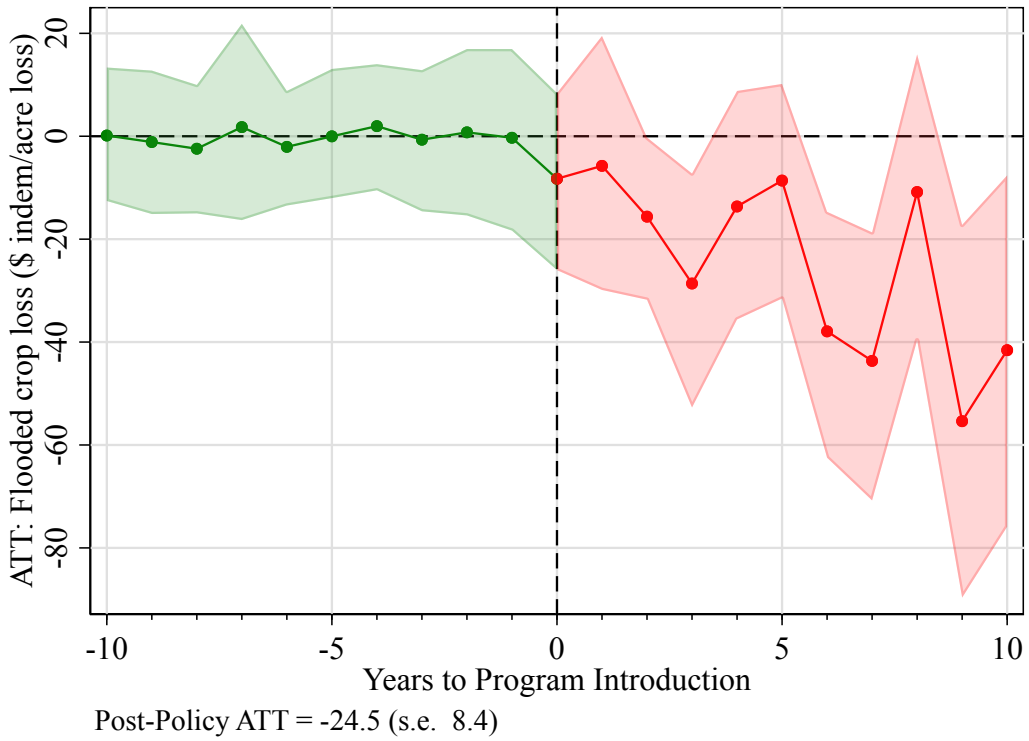


Figure A13. Estimated Impact of CREP Introduction on Flooded Crop Loss (Figure 7 excluding bordering non-CREP counties)

Notes: Excluding non-CREP counties that border with CREP counties, this graph presents the impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss (indemnity payouts per flooded crop acre in 2022 USD value, y-axis) across the number of years to the program introduction (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, flooded crop acres, 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 counties without CREP to construct synthetic controls. Confidence intervals (95%) are constructed using wild bootstrap.

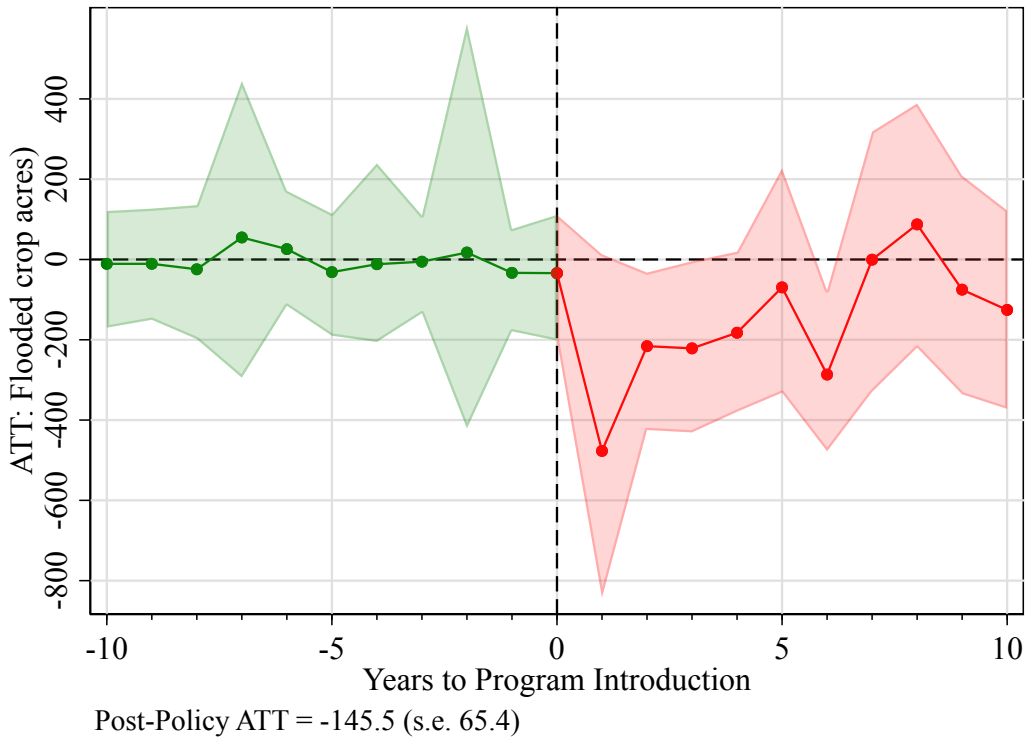


Figure A14. Estimated Impact of CREP Introduction on Crop Acres Flooded (Figure A4 but excluding bordering non-CREP counties)

Notes: Excluding non-CREP counties that border with CREP counties, this graph presents the impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss (indemnity payouts per flooded crop acre in 2022 USD value, y-axis) across the number of years to the program introduction (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, indemnity payout per flooded crop acres, 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 counties without CREP to construct synthetic controls. Confidence intervals (95%) are constructed using wild bootstrap.

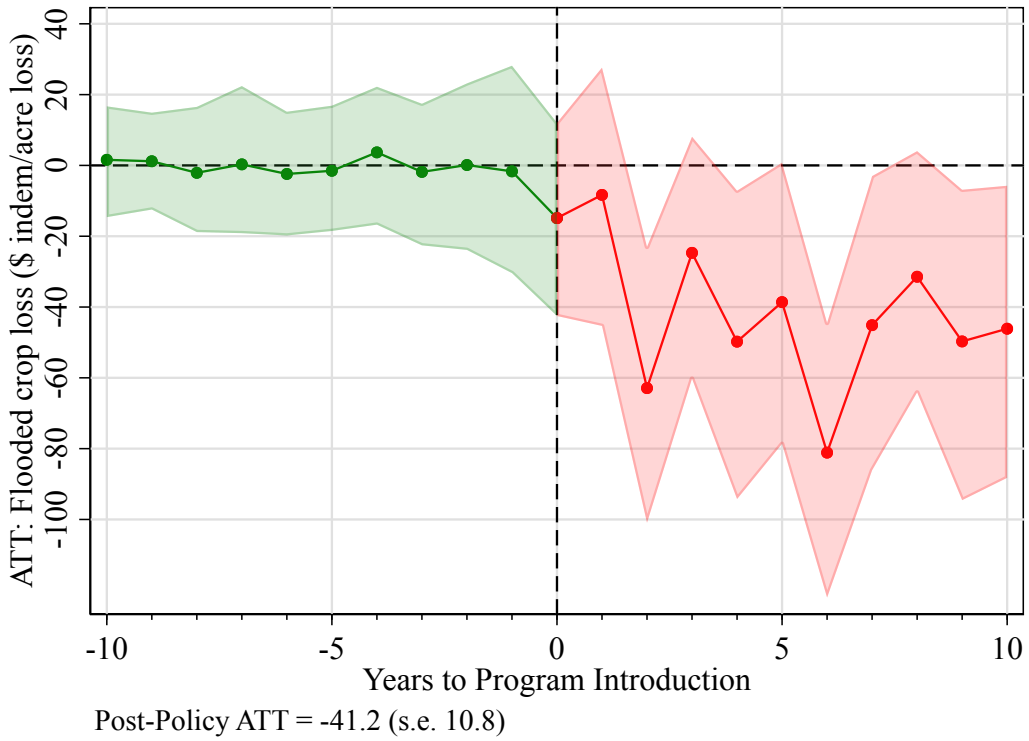


Figure A15. Estimated Impact of CREP Introduction on Indemnity per Flooded Acre (Figure 7 but excluding 1997-2001 CREP cohort)

Notes: Excluding counties where CREP was introduced between 1997 and 2001, this graph presents the impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss (indemnity payouts per flooded crop acre in 2022 USD value, y-axis) across the number of years to the program introduction (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, flooded crop acres, 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 counties without CREP to construct synthetic controls. Confidence intervals (95%) are constructed using wild bootstrap.

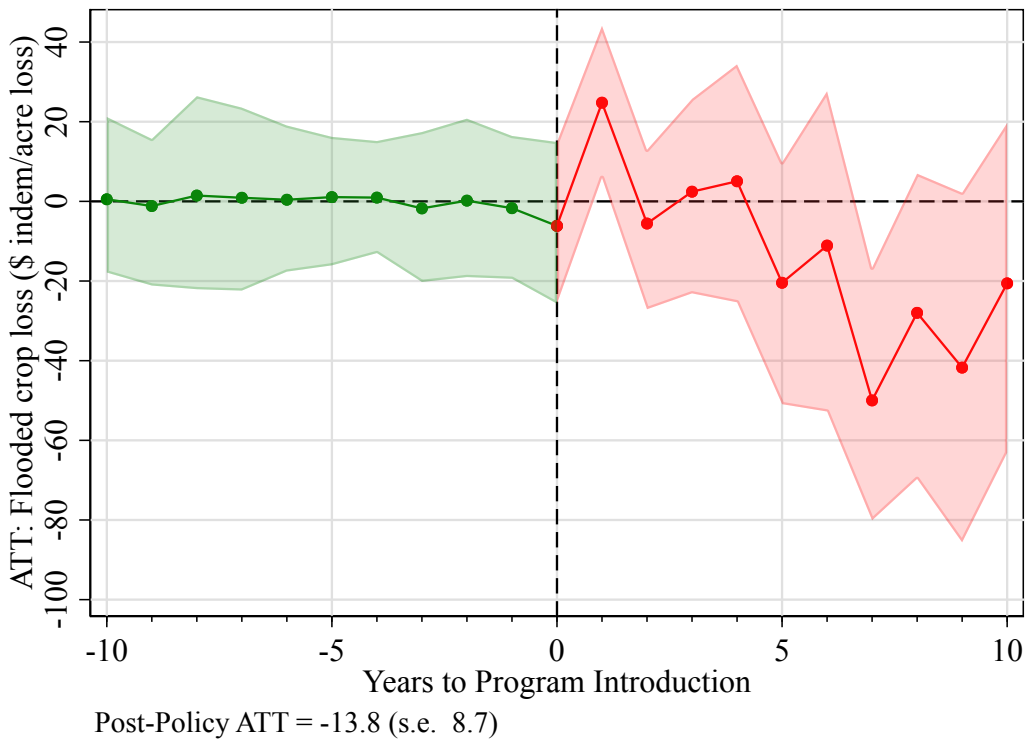


Figure A16. Estimated Impact of CREP Introduction on Indemnity per Flooded Acre (Figure A15 with five year in-time placebo)

Notes: Excluding counties where CREP was introduced between 1997 and 2001 and applying a five-year in-time placebo shift, this graph presents the impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss (indemnity payouts per flooded crop acre in 2022 USD value, y-axis) across the number of years to the program introduction (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, flooded crop acres, 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 counties without CREP to construct synthetic controls. Confidence intervals (95%) are constructed using wild bootstrap.

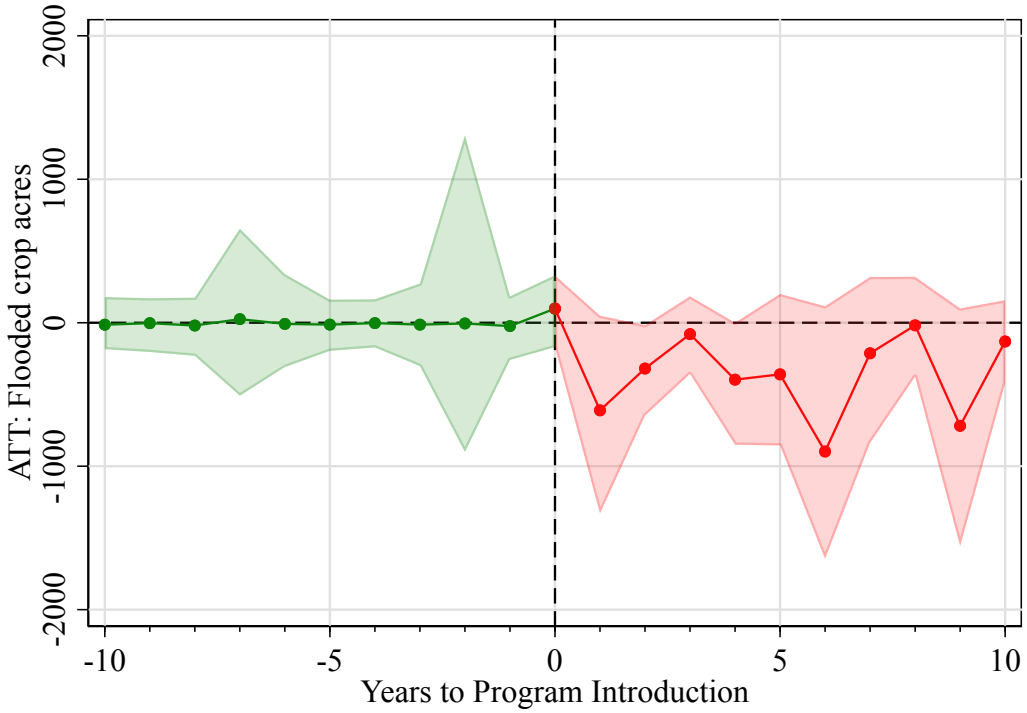


Figure A17. Estimated Impact of CREP Introduction on Crop Acres Flooded (Figure A4 but excluding 1997-2001 CREP cohort)

Notes: Excluding counties where CREP was introduced between 1997 and 2001, this graph presents the impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss (indemnity payouts per flooded crop acre in 2022 USD value, y-axis) across the number of years to the program introduction (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, indemnity payout per flooded crop acre, 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 counties without CREP to construct synthetic controls. Confidence intervals (95%) are constructed using wild bootstrap.

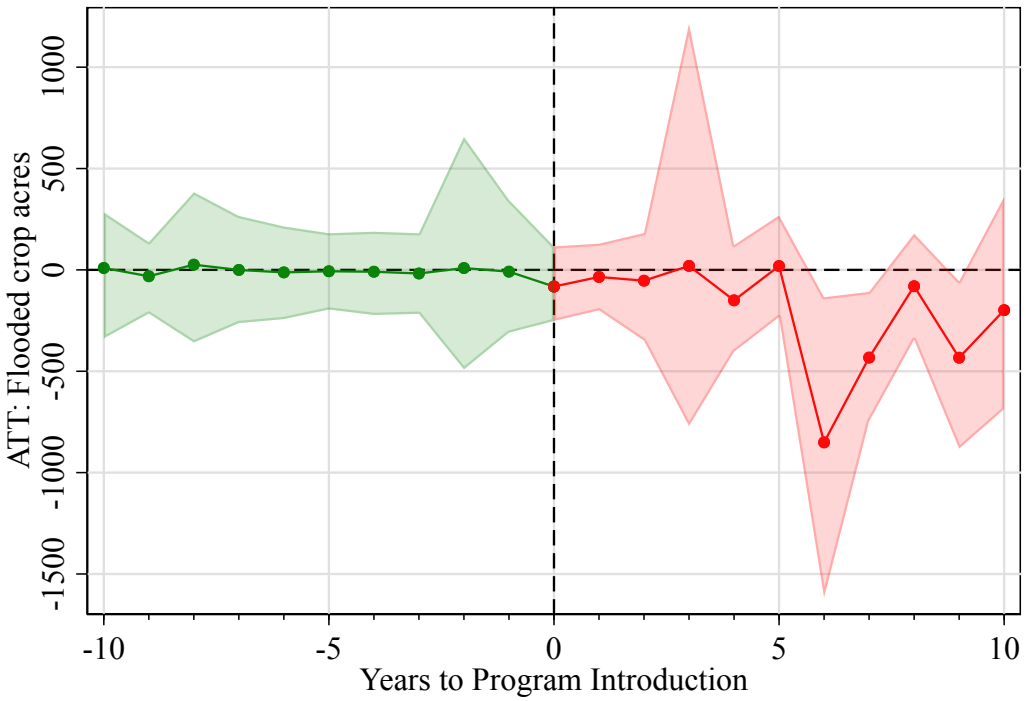
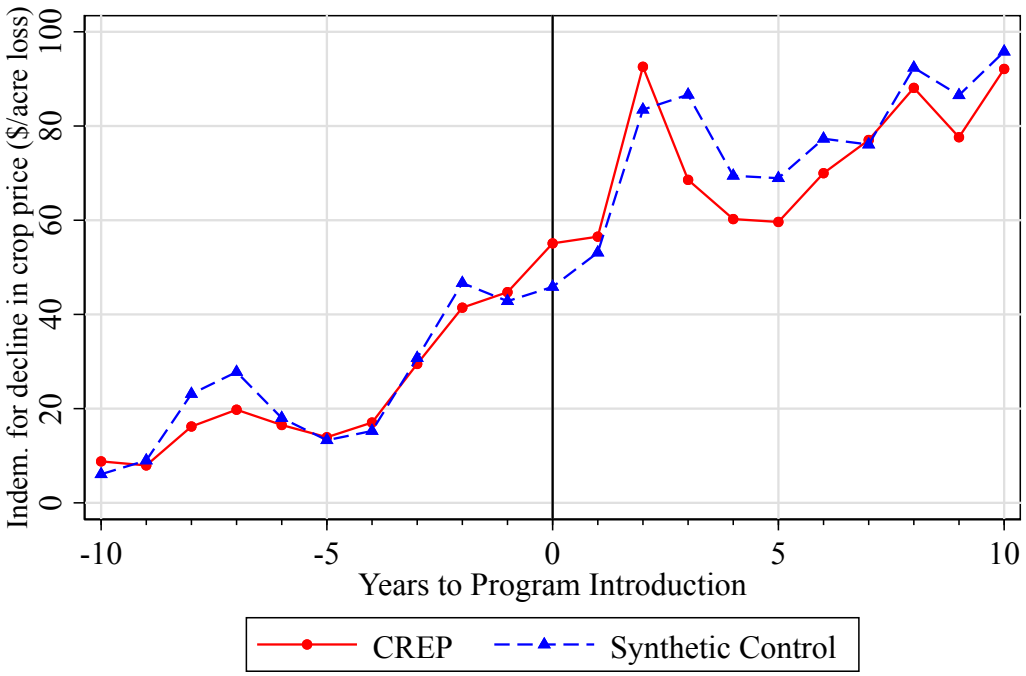


Figure A18. Estimated Impact of CREP Introduction on Crop Acres Flooded (Figure A17 with five year in-time placebo)

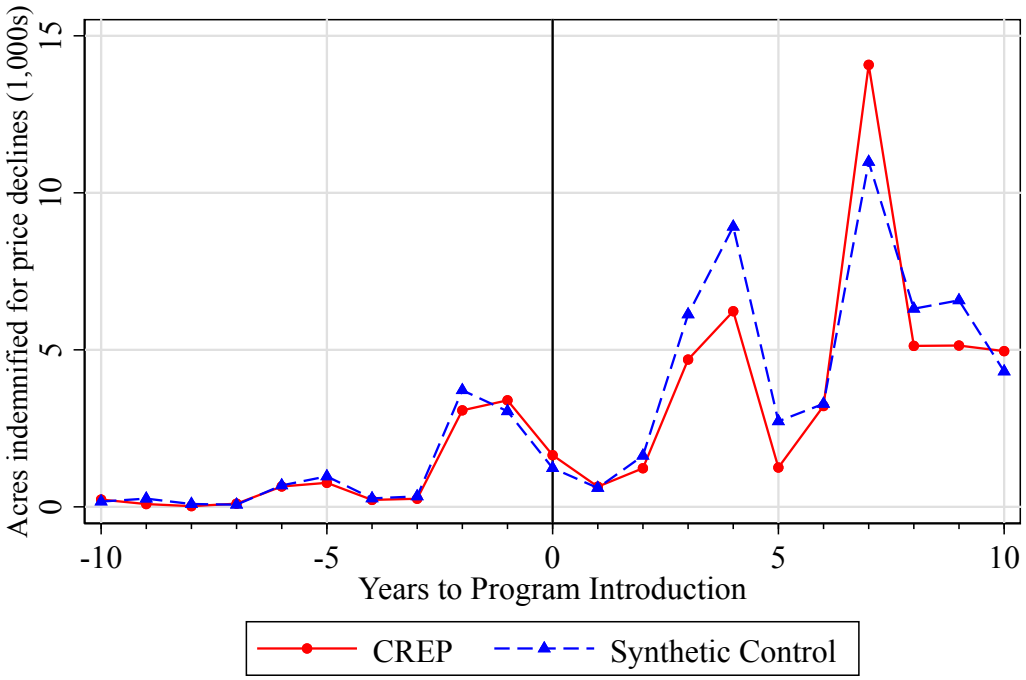
Notes: Excluding counties where CREP was introduced between 1997 and 2001 and applying a five-year in-time placebo shift, this graph presents the impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss (indemnity payouts per flooded crop acre in 2022 USD value, y-axis) across the number of years to the program introduction (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, indemnity payout per flooded crop acre, 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 counties without CREP to construct synthetic controls. Confidence intervals (95%) are constructed using wild bootstrap.



Pre-policy avg.: CREP 22.2, Synthetic control 24, Pre-policy diff. = -1.8
Post-policy avg.: CREP 72.5, Synthetic control 76, Post-policy diff. = -3.5

Figure A19. Trends in Indemnity Payouts per Acre Indemnified for Decline in Crop Price: Counties with CREP and Synthetic Controls

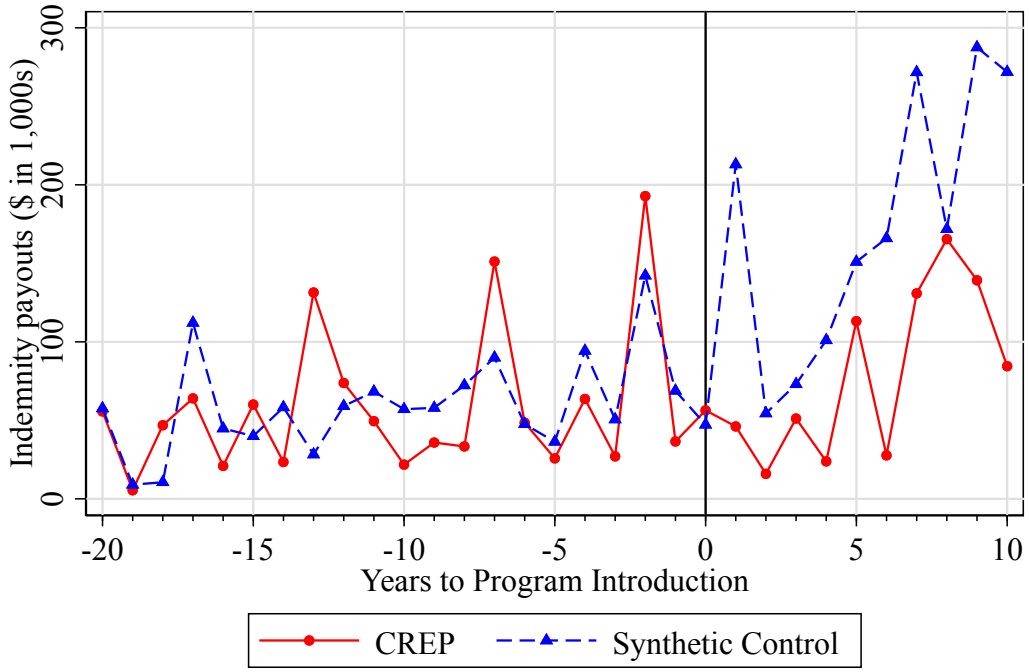
Notes: The graph shows trends in county-level average indemnity payouts per acre indemnified for crop price declines under the federal crop insurance program (y-axis) across the number of years to the program introduction (x-axis) for both 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of counties without CREP.
Source: Author's calculation



Pre-policy avg.: CREP .9, Synthetic control 1, Pre-policy diff. = -.1
Post-policy avg.: CREP 4.4, Synthetic control 4.8, Post-policy diff. = -.4

Figure A20. Trends in Acres Indemnified for Decline in Crop Price: Counties with CREP and Synthetic Controls

Notes: The graph shows trends in county-level average number of crop acres indemnified for price declines under the federal crop insurance program (y-axis) across the number of years to the program introduction (x-axis) for both 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of counties without CREP.
Source: Author's calculation



Pre-policy avg.: CREP 59.5, Synthetic control 65.9, Pre-policy diff. = -6.4
Post-policy avg.: CREP 77.7, Synthetic control 164.4, Post-policy diff. = -86.7

Figure A21. Trends in Indemnity Payouts for Flooded Crop Loss: Counties with CREP and Synthetic Controls

Notes: The graph shows trends in county-level average indemnity payouts due to flooded crop loss for acres insured under the federal crop insurance program (y-axis) across the number of years to the program introduction (x-axis) for both 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of counties without CREP.
Source: Author's calculation

APPENDIX B. SYNTHETIC CONTROL METHOD: SUPPLEMENTARY MATERIALS

The empirical methodology employed to estimate the causal impact of CREP introduction ("treatment") on flooded crop loss utilizes a partially pooled synthetic control method with an intercept shift proposed by Ben-Michael et al. (2022). This approach constructs synthetic control counties for each treated county based on the weighted combination of untreated counties. Then the post-policy trajectory of average outcome for synthetic control counties serves as the counterfactual trajectory of an average crop loss in the treated group. The method allocates weights across untreated counties to minimize two imbalance measures: (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). In this Appendix, I describe the weight allocation procedures in a DID setup based on the work of Ben-Michael et al. (2022).

Let $\gamma_{ij} \geq 0$ denote the weight assigned to untreated county i in constructing 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 weights on untreated counties, and define the N-by-J weight matrix as $\gamma = [\gamma_1, \ldots, \gamma_J] \in \Delta^{scm}$, where $\Delta^{scm} = \Delta_1^{scm} \times \ldots \times \Delta_J^{scm}$. The set of untreated counties includes those where a PES program was never available during the analysis period and those where CREP was not available until $T_j + K$.

The individual fit of outcome $q_Y^{\text{unit}}(\gamma)$ is measured using the root mean square of pre-policy trend fits across treated counties:

$$q_Y^{\text{unit}}(\gamma) \equiv \sqrt{\frac{1}{J}\sum_{j=1}^{J}\frac{1}{L_j}\sum_{l=1}^{L_j}\left[\underbrace{\dot{Y}_{jT_j-l} - \sum_{\substack{i=1 \\ i:T_i>T_j+K}}^{N} \gamma_{ij}\dot{Y}_{iT_j-l}}_{\text{pre-trend diff: individual}}\right]^2}. \qquad (B.1)$$

Similarly, the pooled fit $q_Y^{\text{pool}}(\gamma)$ is measured by the root mean square of the pre-policy trend fits for the average of treated counties:

$$q_Y^{\text{pool}}(\gamma) \equiv \sqrt{\frac{1}{L}\sum_{l=1}^{L}\left[\underbrace{\frac{1}{J}\sum_{T_j>l}\dot{Y}_{jT_j-l} - \frac{1}{J}\sum_{T_j>l}\sum_{\substack{i=1 \\ i:T_i>T_j+K}}^{N}\gamma_{ij}\dot{Y}_{iT_j-l}}_{\text{pre-trend diff: average}}\right]^2}, \qquad (B.2)$$

where $L \equiv max_{j\leq J}L_j$. If a perfect synthetic control unit is found for every treated county, a perfect fit for the average outcome trend of the treated group is achieved (if $q_Y^{\text{unit}}(\gamma) = 0$, then $q_Y^{\text{pool}}(\gamma) = 0$). However, in practice, not all treated units achieve a perfect pre-policy fit, leading to differences in average pre-policy outcome trends between treated and synthetic control counties, potentially affecting the validity of estimated average policy effects. Thus, the partially pooled SCM aims to minimize the imbalance of both individual and pooled outcomes.

Let x_{izt} $(z = 1, \dots Z)$ denote weather conditions z, such as crop growing degree days and precipitation during crop growing and post-harvest seasons, in county i and year t. The pre-policy average value of each covariate z is: $\bar{x}_{iz} \equiv \frac{1}{T_1-1}\sum_{t=1}^{T_1-1}x_{izt}$. The individual and pooled imbalance measures for covariates are defined as:

$$q_X^{\text{unit}}(\gamma) \equiv \sqrt{\frac{1}{J}\sum_{j=1}^{J}\left[\sum_{z=1}^{Z}\left(\bar{x}_{jz} - \sum_{\substack{i=1 \\ i:T_i>T_j+K}}^{N}\gamma_{ij}\bar{x}_{iz}\right)^2\right]}, \qquad (B.3)$$

and

$$q_X^{\text{pool}}(\gamma) \equiv \sqrt{\sum_{z=1}^{Z}\left[\frac{1}{J}\sum_{j=1}^{J}\bar{x}_{jz} - \frac{1}{J}\sum_{j=1}^{J}\sum_{\substack{i=1 \\ i:T_i>T_j+K}}^{N}\gamma_{ij}\bar{x}_{iz}\right]^2}. \qquad (B.4)$$

The partially pooled SCM aims to find a set of weights γ that minimizes the weighted sum of both individual and pooled imbalance terms as follows:

$$\min_{\gamma\in\Delta^{\text{scm}}} \nu_Y\left[q_Y^{\text{pool}}(\gamma)^2 + \nu_X q_X^{\text{pool}}(\gamma)^2\right] + (1-\nu_Y)\left[q_Y^{\text{unit}}(\gamma)^2 + \nu_X q_X^{\text{unit}}(\gamma)^2\right] + \lambda\|\gamma\|_F^2. \qquad (B.5)$$

The relative importance of the pooled fit to individual fit increases with ν_Y and the importance of covariate balance increases with ν_X. To ensure unique weights and mitigate interpolation biases, a regularization penalty term λ is included (Abadie et al., 2015; Doudchenko & Imbens, 2016;

Abadie & L'Hour, 2021; Arkhangelsky et al., 2021). The penalty term is applied to the square root of the sum of the absolute squares of elements in the matrix, where $\|\cdot\|_F$ is Frobenius norm (e.g., $\|\gamma\|_F^2 = \sum_i \sum_j \gamma_{ij}^2$). Overall, the synthetic control counties likely consist of untreated counties with similar weather conditions and trends in flood damage compared to the treated counties, except for the introduction of CREP.

In practice, q_Y^{unit} and q_X^{unit} are normalized by $\sqrt{q_Y^{\text{unit}}(\hat{\gamma}^{\text{unit}})^2 + \nu_X q_X^{\text{unit}}(\hat{\gamma}^{\text{unit}})^2}$. Similarly, q_Y^{pool} and q_X^{pool} are normalized by $\sqrt{q_Y^{\text{pool}}(\hat{\gamma}^{\text{unit}})^2 + \nu_X q_X^{\text{pool}}(\hat{\gamma}^{\text{unit}})^2}$, where $\hat{\gamma}^{\text{unit}}$ is the set of weights $\gamma_1, \ldots, \gamma_J$ that solves the following optimization problem, which minimizes the imbalance of individual pre-policy fit only:

$$\min_{\gamma \in \Delta^{\text{scm}}} \left[q_Y^{\text{unit}}(\gamma)^2 + \nu_X q_X^{\text{unit}}(\gamma)^2 \right] + \lambda \|\gamma\|_F^2 . \qquad (B.6)$$

I follow Ben-Michael et al. (2022) and set ν_Y as the ratio of pooled fit to the average unit-level fit and set ν_X as the sample variance of outcomes for never-treated units during T_J periods.

Using the set of weights $\hat{\gamma}_{ij}$ obtained from the objective function (B.5), I obtain the estimated counterfactual average outcome of county j treated in year T_j at event time k as follows:

$$\hat{Y}_{jT_j+k}(\infty) = \underbrace{\frac{1}{L_j}\sum_{l=1}^{L_j} Y_{jT_j-l} - \frac{1}{L_j}\sum_{i=1, i\neq j}^{N}\sum_{l=1}^{L_j} \hat{\gamma}_{ij} Y_{iT_j-l}}_{\text{intercept shift}} + \underbrace{\sum_{i=1, i\neq j}^{N} \hat{\gamma}_{ij} Y_{iT_j+k}}_{\text{weighted average of untreated outcome}} , \qquad (B.7)$$

where the intercept shift represents the average pre-policy outcome difference between treated county j and its synthetic control county. By combining equations (B.7) with (8), I obtain the weighted DID estimator $\hat{\tau}_{jk}$:

$$\hat{\tau}_{jk} = \dot{Y}_{jT_j+k}(T_j) - \hat{\dot{Y}}_{jT_j+k}(\infty) \qquad (B.8)$$

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

REFERENCES

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

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

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

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

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

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

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

Aglasan, S., Rejesus, R. M., Hagen, S., & Salas, W. (2023). Cover crops, crop insurance losses, and resilience to extreme weather events. *American Journal of Agricultural Economics*.

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

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

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

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

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

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

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

Baumgärtner, S., & Strunz, S. (2014). The economic insurance value of ecosystem resilience. *Ecological Economics*, 101, 21–32.

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

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

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

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

Bigelow, D., Claassen, R., Hellerstein, D., Breneman, V., Williams, R., & You, C. (2020). *The Fate of Land in Expiring Conservation Reserve Program Contracts, 2013-16*. Economic Information Bulletin Number 215. Washington, DC: U.S. Department of Agriculture, Economic Research Service.

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

Bourgeon, J. M., & Picard, P. (2024). Self-insurance and market insurance substitutability: an established tenet reconsidered. 2024. hal-04401333

Bradt, J.T., & Aldy, J.E. (2022). Private benefits from public investment in climate adaptation and resilience. Working paper.

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

Bundy, L.R., Gensini, V.A., & Russo, M.S. (2022). Insured corn losses in the United States from weather and climate perils. *Journal of Applied Meteorology and Climatology*, *61*(8), 969–988.

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

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

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

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

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

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

Cattaneo, M. D., Feng, Y., Palomba, F., & Titiunik, R. (2022). Uncertainty quantification in synthetic controls with staggered treatment adoption. ArXiv Preprint ArXiv:2210.05026.

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

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

Claassen, R., Langpap, C., & Wu, J. (2017). Impacts of federal crop insurance on land use and environmental quality. *American Journal of Agricultural Economics*, *99*(3), 592–613. http://dx.doi.org/10.1093/ajae/aaw075

Coble, K., & Barnett, B. (2013). Why do we subsidize crop insurance? *American Journal of Agricultural Economics*, *95*(2), 498–504.

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

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

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

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

de Chaisemartin, C., & D'Haultfoeuille, X. (2024). Difference-in-differences estimators of intertemporal treatment effects. *Review of Economics and Statistics*, 1-45.

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

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

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

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

Ehrlich, I., & Becker, G. S. (1972). Market insurance, self-insurance, and self-protection. *Journal of Political Economy*, 80(4), 623–648.

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

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

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

FEMA, (2025). National Flood Hazard Layer (NFHL) 20251019. Federal Emergency Management Agency.

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

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

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

Fischer, C., & Preonas, L. (2010). Combining policies for renewable energy: Is the whole less than the sum of its parts? *International Review of Environmental and Resource Economics*, *4*(1), 51–92. https://doi.org/10.1561/101.00000030

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

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

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

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

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

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

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

Goodwin, B. K., & Piggott, N. E. (2020). Has technology increased agricultural yield risk? Evidence from the crop insurance biotech endorsement. *American Journal of Agricultural Economics*, *102*(5), 1578–1597.

Hansen, L. (2007). Conservation reserve program: Environmental benefits update. *Agricultural and Resource Economics Review*, *36*(2), 267–280.

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

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

Johnson, K. A., Dalzell, B. J., Donahue, M., Gourevitch, J., Johnson, D. L., Karlovits, G. S., Keeler, B., & Smith, J. T. (2016). Conservation Reserve Program (CRP) lands provide ecosystem service benefits that exceed land rental payment costs. *Ecosystem Services*, *18*, 175–185.

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

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

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

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

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

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

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

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

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

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

Manning, D. T., Rad, M. R., Suter, J. F., Goemans, C., Xiang, Z., & Bailey, R. (2020). Non-market valuation in integrated assessment modeling: The benefits of water right retirement. *Journal of Environmental Economics and Management*, *103*, 102341.

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

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

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

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

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

Moore, M.R., & Huang, H.H. (2019). 3. Farming under weather risk: adaptation, moral hazard, and selection on moral hazard. In *Agricultural Productivity and Producer Behavior* (pp. 77–124). University of Chicago Press.

Narayan, S., Beck, M. W., Wilson, P., Thomas, C. J., Guerrero, A., Shepard, C. C., Reguero, B. G., Franco, G., Ingram, J. C., & Trespalacios, D. (2017). The value of coastal wetlands for flood damage reduction in the northeastern USA. *Scientific Reports*, *7*(1), 9463.

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

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

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

Pates, N. J., & Hendricks, N. P. (2020). Additionality from payments for environmental services with technology diffusion. *American Journal of Agricultural Economics*, *102*(1), 281-299.

Perry, E. D., Yu, J., & Tack, J. (2020). Using insurance data to quantify the multidimensional impacts of warming temperatures on yield risk. *Nature Communications*, *11*(1), 4542.

Pfaff, A., & Robalino, J. (2017). Spillovers from conservation programs. *Annual Review of Resource Economics*, *9*, 299–315.

Prokopy, L. S., Floress, K., Arbuckle, J. G., Church, S.P., Eanes, F.R., Gao, Y., Gramig, B.M., Ranjan, P., & Singh, A.S. (2019). Adoption of agricultural conservation practices in the United States: Evidence from 35 years of quantitative literature. *Journal of Soil and Water Conservation*, *74*(5), 520–534.

Quaas, M. F., & Baumgärtner, S. (2008). Natural vs. financial insurance in the management of public-good ecosystems. *Ecological Economics*, 65(2), 397–406.

Quaas, M. F., Baumgärtner, S., & Klein, A.-M. (2019). Insurance value of natural capital. *Ecological Economics*, 165, 106388.

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

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

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

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

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

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

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

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

Schlenker, W., & Roberts, M.J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences*, *106*(37), 15594. http://www.pnas.org/content/106/37/15594.abstract

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

Sears, J., Villas-Boas, J. M., Villas-Boas, S. B., & Villas-Boas, V. (2023). Are we# stayinghome to flatten the curve? *American Journal of Health Economics*, *9*(1), 71–95.

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

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

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

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

United States Army Corps of Engineers (USACE), National Levee Database (NLD), 20251018. Online Access: https://levees.sec.usace.army.mil/.

United States Department of Agriculture (USDA), Economic Research Service (ERS). 2018. Projected outlays under the 2018 Farm Act, 2019-2023 based on Congressional Budget Office, Direct Spending Effects for the Agriculture Improvement Act of 2018, Decemeber 11, 2018.

United States Department of Agriculture (USDA), Farm Service Agency (FSA). 2023. Conservation Reserve Program Annual Summary, 2011-2022.

United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS), 20240131, Cropland Data Layer: USDA NASS, USDA NASS Marketing and Information Services Office, Washington, D.C.

Wang, H. (2021). Flood your neighbors: spillover effects of levee building. Working Paper.

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

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

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

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

Woznicki, S. A., Baynes, J., Panlasigui, S., Mehaffey, M., & Neale, A. (2019). Development of a spatially complete floodplain map of the conterminous United States using random forest. *Science of the Total Environment*, *647*, 942–953.

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

Wu, J. (2000). Slippage effects of the conservation reserve program. *American Journal of Agricultural Economics*, *82*(4), 979–992.

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

Wu, Y., Sun, J., Hu, B., Zhang, G., & Rousseau, A. N. (2023). Wetland-based solutions against extreme flood and severe drought: Efficiency evaluation of risk mitigation. *Climate Risk Management*, *40*, 100505.

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

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