ABSTRACT

Title of Dissertation:	ESSAYS ON THE DESIGN AND EVALUATION OF PAYMENTS FOR ECOSYSTEM SERVICES PROGRAMS
	Youngho Kim, Doctor of Philosophy, 2024
Dissertation directed by:	Professor Erik Lichtenberg Department of Agricultural and Resource Economics
	Associate Professor David A. Newburn Department of Agricultural and Resource Economics

Nature-based solutions for climate change mitigation and adaptation emphasize the restoration of natural infrastructure and the adoption of conservation practices in agriculture. Payment for ecosystem services (PES) programs play a key role in these efforts by offering financial incentives to farmers and landowners who adopt land use or management activities that provide environmental amenities and services for society. This dissertation consists of three chapters that examine the optimal design of PES programs and evaluate their performance in the context of climate change and environmental protection.

The first chapter investigates whether PES programs contribute to climate change adaptation by reducing economic losses from extreme weather events. I evaluate the cost-effectiveness of the Conservation Reserve Enhancement Program (CREP) in the United States in mitigating flooded crop losses through the restoration of riparian buffers and wetlands. By leveraging variation in the

timing of program introduction across counties in the Mississippi River Basin, I find that the introduction of CREP reduced both the number of flooded acres and the extent of damage on those acres. CREP also generated financial spillover effects on the federal crop insurance program, reducing indemnity payouts that would have otherwise been allocated to insured farmers. This study enhances our understanding of how PES programs promote sustainable agriculture and facilitate nature-based solutions for climate change adaptation.

The second chapter examines the cost-effective structure of payments and penalties in PES programs, in collaboration with Erik Lichtenberg and David Newburn. The sustainability of ecosystem services programs is contingent on landowners' compliance with the signed contracts after their initial participation. However, premature contract terminations are not uncommon, particularly when unexpected increases in crop prices lead to the removal of established conservation cover on agricultural land. In such cases, PES programs typically require participants to repay all payments received up to the date of contract termination (e.g., those in the US, the EU, Costa Rica, Mexico, Australia, and many other countries). This standard penalty structure is inefficient because it directly couples penalties with payments, increasing monotonically during the contract period. This study is the first to derive the optimal penalty structure that equals net environmental benefits for the remaining contract period, which decouples penalties from payments. A numerical policy simulation using integrated assessment models shows that the U.S. federal PES programs can substantially increase the environmental benefits by restructuring the current standard penalty. Importantly, the optimal penalty tends to decrease gradually during the contract period, providing credit to farmers for the ecosystem services generated prior to the contract termination. This finding has broad implications for restructuring PES programs in the

U.S. and globally, and the study has been published in the *Journal of Environmental Economics and Management*.

The third chapter examines the influence of U.S. federal agricultural conservation programs on the performance of emissions trading programs in promoting afforestation activities on agricultural land, in collaboration with Erik Lichtenberg, David Newburn, Haoluan Wang, and Derek Wietelman. Emissions trading programs, which pay for performance, have been advocated as flexible and efficient tools for achieving pollution reduction goals when evaluated in isolation. However, these programs often operate within a policy landscape dominated by conservation subsidy programs that pay for effort. We find that current federal conservation subsidies are so generous that they significantly crowd out water trading programs when both are in competition, although water trading programs would be effective in isolation. In addition, current carbon market payments for offsets are insufficient to make emissions trading programs more attractive compared to longstanding agricultural conservation subsidy programs. While prior studies have attributed low farmer participation in emissions trading programs to transaction costs and market uncertainty, our analysis suggests that even if these impediments are removed, competition with existing pay-for-effort programs would remain a significant barrier to expansion of emissions trading among agricultural producers. Therefore, the attractiveness and effectiveness of emissions trading programs for afforestation depend heavily on the presence and generosity of longstanding federal agricultural conservation subsidies.

ESSAYS ON THE DESIGN AND EVALUATION OF PAYMENTS FOR ECOSYSTEM SERVICES PROGRAMS

by

Youngho Kim

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2024

Advisory Committee:
Professor Erik Lichtenberg, Co-Chair
Associate Professor David A. Newburn, Co-Chair
Professor Erich Battistin
Associate Professor Jorge Holzer
Professor Maureen Cropper

© Copyright by
Youngho Kim
2024

Foreword

The first chapter is sole-authored work. The second chapter, a pre-publication draft of our research article in the *Journal of Environmental Economics and Management* (Volume 126, July 2024, 102988), is jointly authored with Erik Lichtenberg and David A. Newburn. The third chapter is jointly authored with Erik Lichtenberg, David A. Newburn, Haoluan Wang, and Derek Wietelman. The Dissertation Committee acknowledges that Youngho Kim made substantial contributions to relevant aspects of the second and third chapters, as affirmed by the coauthors on each project.

Dedication

To my family.

Acknowledgements

This dissertation would not have been possible without the support, guidance, and encouragement of many individuals, to whom I am deeply grateful. I wish to highlight a few of them in this section.

I express my deepest gratitude to my advisors, Erik Lichtenberg and David Newburn, for their invaluable guidance and support throughout my Ph.D. journey. I am also profoundly thankful to Erich Battistin, who opened my eyes to the world of causal inference. Their mentorship has been instrumental in my development as an applied microeconomist, and I will remain deeply indebted to them for a very long time.

I extend my sincere thanks to Joshua Linn, Jorge Holzer, Cory Smith, Sharan Mamidipudi, James Archsmith, Rebecca Epanchin-Niell, Louis Preonas, Neslihan Uler, Lori Lynch, and Maureen Cropper for their constructive suggestions and generous sharing of their time and knowledge.

I would also like to express my gratitude to Richard Woodward, Senarath Dharmasena, Joe Outlaw, John Siebert, Ximing Wu, and Steven Ward for their invaluable support during my undergraduate studies, which laid the foundation for my Ph.D. program.

Special thanks go to my colleagues and friends at the University of Maryland, especially my AREC cohort (Daniel Kraynak, Zed Higgs, Alejandro Lopez, Lauren Beatty, Sam Williamson, and Alex Perrault), Junhyun Lee, Keehyun Park, Changmin Lee, Haoluan Wang, Derek Wietelman, and Michael Gibson, for their support and for making this journey enjoyable and enriching.

Lastly, I extend my heartfelt appreciation to my family. To my parents and brothers, your love, support, and encouragement have been my foundation. To my spouse, Yoni, thank you for standing by my side through every challenge and triumph.

Thank you all for being a part of this journey.

Table of Contents

Foreword ii
Dedication iii
Acknowledgements iv
Table of Contents vi
List of Tables viii
List of Figures ix
Chapter 1: Payments for Ecosystem Services Programs and Climate Change Adaptation in Agriculture 1
1.1 Introduction 1
1.2 Background and Institutional Context 7
1.2.1 Flood Risk Management: Gray and Green Infrastructure 7
1.2.2 Payments for Ecosystem Services Program 9
1.2.3 Conservation Reserve Enhancement Program 10
1.2.4 Crop Loss Covered under the Federal Crop Insurance Program 12
1.3 Theoretical Framework 14
1.3.1 Farmer's Land Use Decision 15
1.3.2 Establishing Natural Infrastructure Through PES Programs 17
1.3.3 Loss Mitigating Benefits of PES programs 18
1.4 Data 19
1.4.1 Conservation Reserve Enhancement Program 20
1.4.2 Flood Damage on Cropland 27
1.4.3 Weather 29
1.5. Empirical Framework 30
1.5.1 Estimands of Interest 30
1.5.2 Identification Strategy 32
1.5.3 Synthetic Control Method 36
1.6 Results 38
1.6.1 Flood Mitigation Benefits of CREP Introduction 38
1.6.2 Confounding Factors 44
1.6.3 Placebo Test 45
1.6.4 Sensitivity Analysis 46
1.6.5 Decomposing the Flood Mitigation Benefits: Conversion and Protection Effects 48
1.7 Program Effect Heterogeneity 50
1.7.1 Nature-based Infrastructure Established through CREP 53
1.7.2 Inter-County Spillover Effects 53
1.7.3 Upstream versus Downstream Farm Resource Regions 54
1.7.4 Presence of Infrastructure for Flood Mitigation 54
1.7.5 Crop Insurance Adoption 55
1.7.6 Community Resilience to Natural Disaster 56
1.8 Conclusion 57
Chapter 2: Payments and Penalties in Ecosystem Services Programs 60

2.1 Introduction 60
2.2 Theoretical Framework 66
2.2.1 Model Setup 68
2.2.2 Two-period PES Contract 71
2.3 Numerical Policy Simulation Methods 90
2.3.1 Landowner's Opportunity Cost of Land 92
2.3.2 Riparian Buffer Installation and Removal Cost 94
2.3.4 Contract Terms Offered 98
2.3.5 Simulated Contract Performance 98
2.4 Policy Simulation Results 99
2.4.1 Contract Terms 100
2.4.2 Contract Performance 102
2.4.3 Sensitivity Analysis: Environmental Benefits with Uncertainty 107
2.5 Conclusion 111
Chapter 3. Emissions Trading Programs for Afforestation: Interactions 115
with Federal Agricultural Conservation Programs 115
3.1 Introduction 115
3.2 Stated Preference Study 120
3.2.1 Empirical Framework 120
3.2.2 Survey Design and Implementation 122
3.2.3 Estimation Results 126
3.3 Policy Simulation 130
3.3.1 Environmental benefits 132
3.3.2 Program Types and Attributes 136
3.3.3 Policy Simulation Method 142
3.4 Policy Simulation Results 145
3.5 Conclusion 149
Appendix A: Appendices to Chapter 1 152
A1. Supplementary Tables and Figures 152
A2. Synthetic Control Method: Supplementary Materials 172
Appendix B: Appendices to Chapter 2 175
B1. Derivation of the Optimal Multi-Period Contract 175
B2. Calculating the Environmental Benefits of Riparian Buffers 178
B3. Calculating The Opportunity Cost of Land 185
B4. Sensitivity Analysis: Interest Rate 188
Appendix C: Appendices to Chapter 3 189
C1. Calculating Carbon Sequestration Benefits of Riparian Forest Buffers 189
Bibliography 197

List of Tables

Table 1.1 Descriptive Statistics: Main Analysis 21
Table 1.2 Descriptive Statistics: Heterogeneity Analysis 51
Table 1.3 Program Effect Heterogeneity 52

Table 2.1 Simulation results for baseline scenario 105
Table 2.2 Parcel characteristics by enrollment type 106
Table 2.3 Simulation results: Sensitivity analysis using environmental benefits with uncertainty 110

Table 3.1 Descriptions of Program Attributes in a Discrete Choice Experiment 124
Table 3.2 Description of Variables from the Survey and Summary Statistics 127
Table 3.3 Logit Estimation for Enrollment in Riparian Buffer Program: Discrete Choice Experiment 128
Table 3.4 Summary Statistics of Program Attributes in Baseline Policy Simulation 146
Table 3.5 Policy Simulation Results 147

Table A1. Descriptive Statistics by CREP Availability: Main Analysis 152
Table A2. Timing Variation of Conservation Reserve Enhancement Program (CREP) Availability and Participation 153
Table A3. Estimated Impact of CREP Introduction on Flood Damage on Cropland 154

Table B1. Summary of Simulation Results: Higher Interest Rate 188

List of Figures

Figure 1.1 Spatial and Temporal Variation in the Introduction of CREP: Heartland and Mississippi River Portal Regions 23
Figure 1.2 Conservation Reserve Enhancement Program: Timing Variation of Introduction and Participation across Counties, 1998-2022 24
Figure 1.3 Conservation Reserve Enhancement Program: Enrolled Acres and Program Spending by Event Time 25
Figure 1.4 Trends in Flooded Crop Loss in the Federal Crop Insurance Program, 1998-2022: Counties with versus without Conservation Reserve Enhancement Program 29
Figure 1.5 Spatial Distribution of Synthetic Control Weights Allocated to Untreated Counties 40
Figure 1.6 Trends in Flooded Crop Loss: Counties with CREP and Synthetic Controls 41
Figure 1.*7* Estimated Impact of CREP Introduction on Flooded Crop Loss 42

Figure 2.1 Land-use path: Two-period PES contract 72
Figure 2.2 Land-use path: Multi-period PES contract 79
Figure 2.3 Distribution of the random shock 95
Figure 2.4 Standard and optimal non-completion penalty schedules 101

Figure 3.1 An Illustrative Example of a Discrete Choice Experiment Question 125

Figure A1. Spatial Heterogeneity of Flood Damage on Cropland Before 1998: Heartland and Mississippi River Portal Regions 155
Figure A2. Trends in Indemnity Payouts due to Flooded Crop Loss: Counties with CREP and Synthetic Controls 156
Figure A3. Trends in Crop Acres Flooded: Counties with CREP and Synthetic Controls 157
Figure A4. Trends in Acres Insured under the Federal Crop Insurance Program: Counties with CREP and Synthetic Controls 158
Figure A5. Trends in Insurance Coverage Level under the Federal Crop Insurance Program: Counties with CREP and Synthetic Controls 159
Figure A6. Trends in Precipitation during Crop Growing Season: Counties with CREP and Synthetic Controls 160
Figure A7. Trends in Growing Degree Days (10-29 Celsius) during Crop Growing Season: Counties with CREP and Synthetic Controls 161
Figure A8. Trends in Acreage enrolled under the Conservation Reserve Program (excluding CREP) : Counties with CREP and Synthetic Controls 162
Figure A9. Trends in Acreage enrolled under the Agricultural Conservation Easement Program's Wetland Reserve Easement: Counties with CREP and Synthetic Controls 163
Figure A10. Trends in Indemnity Payouts due to Decline in Crop Price: Counties with CREP and Synthetic Controls 164

Figure A11. Estimated Impact of CREP Introduction on Flooded Crop Loss (ATT without weather covariates) 165
Figure A12. Estimated Impact of CREP Introduction on Flooded Crop Loss (ATT: up to 21 event times)..... 166
Figure A13. Estimated Impact of CREP Introduction on Flooded Crop Loss (ATT: IHS)..... 167
Figure A14. Estimated Impact of CREP Introduction on Flooded Crop Loss (ATT: Loss Cost) 168
Figure A15. Estimated Impact of CREP Introduction on Flooded Crop Loss (ATT: alternative screening criteria for the analysis counties)..... 169
Figure A16. Estimated Impact of CREP Introduction on Flooded Crop Loss (ATT: Callaway and Sant'Anna (2021) without weather covariates) 170
Figure A17. Estimated Impact of CREP Introduction on Flooded Crop Loss (ATT: Callaway and Sant'Anna (2021) with weather covariates)..... 171

Figure B1. Efficiency Rate of the Riparian Grass Buffer by Pollutant Type 182
Figure B2. Time Profile of Annual Environmental Benefits of Converting Cropland to Grass Riparian Buffer 184

Chapter 1: Payments for Ecosystem Services Programs and Climate Change Adaptation in Agriculture

1.1 Introduction

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

PES programs have been widely implemented to provide a variety of environmental services to society, such as the reduction of agricultural nonpoint source water pollution, carbon sequestration benefits, and restoration of wildlife habitats (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 conservation practices can build resilience to extreme weather events associated with climate change, such as floods and droughts (Kousky & Walls, 2014; Michler et al., 2019; Taylor & Druckenmiller, 2022; Aglasan et al., 2023). For instance, the restoration of riparian buffers and wetlands on agricultural land can attenuate regional flood risks by absorbing excess water and slowing down the flow of floodwaters (Delgado

et al., 2011; Acreman & Holden, 2013; Brody & Highfield, 2013; Croke et al., 2017). However, research on the cost-effectiveness of implementing PES programs for climate change adaptation remains limited.

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

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

My empirical analysis exploits county-level spatial and temporal variation in the introduction of CREP and flood damage on cropland across 400 counties in the Mississippi River Basin from

1989 to 2022. The analysis utilizes administrative data obtained from the United States Department of Agriculture (USDA)'s Farm Service Agency (FSA) and Risk Management Agency (RMA). In an ideal experiment for assessing the flood mitigation benefits of CREP, we would compare flood damage on cropland between counties that are identical in all respects, except for the presence of CREP.

However, my identification strategy faces two empirical challenges. First, the availability of CREP may be associated with other factors that contribute to flood damage on cropland. For example, the government may implement CREP in regions vulnerable to frequent flooding on cropland, given the significant water quality benefits associated with converting cropland to riparian buffers and wetlands. Second, the variation in the timing of CREP introduction across counties, along with potentially heterogeneous program effects, requires a careful selection of a comparison group in estimating causal effects. For instance, the conventional two-way fixed effects difference-in-differences (DID) estimator may introduce bias to the estimated program effect (Borusyak et al., 2021; Goodman-Bacon, 2021; Baker et al., 2022; Roth et al., 2023).

To address these challenges, my identification strategy leverages the staggered rollout of CREP across counties. In estimating the flood mitigation benefits of CREP, I consider two approaches for implementing DID with staggered program introduction: (i) a weighted average of DID estimates by the cohort of program adoption (de Chaisemartin & d'Haultfoeuille, 2020; Callaway & Sant'Anna, 2021; Sun & Abraham, 2021) and (ii) an average of county-specific DID estimates by leveraging the county-specific variation in the year of program introduction (Arkhangelsky et al., 2021; Ben-Michael et al., 2022). I implement the latter approach and construct a comparison group for each county with CREP availability using a synthetic control method (SCM) (Abadie & Gardeazabal, 2003; Abadie et al., 2010, 2015). The program effect estimator takes the form of a

weighted DID estimator that aims to compare counties with 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 heterogeneity across counties, such as inherent production risks, and (ii) the program effect heterogeneity in the setting of staggered program adoption. To assess the robustness of the findings, I also estimate the program effect using the staggered DID estimator proposed by Callaway and Sant'Anna (2021).

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

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

while the remaining benefits resulted from taking at-risk cropland out of production for conservation purposes.

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

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

associated with the introduction of CREP, which has spent billions of dollars in restoring natural infrastructure nationwide since 1998.

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

Finally, this study has important implications for future research and existing policies. Existing analyses on the cost-effectiveness of PES programs have mainly compared additional environmental benefits to program payments (Ferraro & Simpson, 2002; Lichtenberg & Smith-Ramirez, 2011; Mezzatesta et al., 2013; Claassen et al., 2018; Fleming et al., 2018; Lichtenberg, 2021). In addition to the environmental benefits, future analyses should also consider (i) the long-term benefits of building resilience against adverse weather conditions and (ii) the economic

spillover effects on disaster assistance programs. For instance, this study reveals that CREP's flood mitigation benefits in agriculture amount to 21 percent of the program expenditure, primarily driven by the protection services of established natural infrastructure. Similarly, prior research revealed spatial spillovers in the flood mitigation benefits associated with floodplain conservation and wetlands, extending to residential properties and cropland (Kousky and Walls, 2014; Karwowski, 2022; Taylor & Druckenmiller, 2022). Thus, incorporating these loss mitigating benefits would provide a comprehensive evaluation of PES programs, as weather anomalies and government-funded disaster payouts are expected to increase in the future (Tack et al., 2018; Reyes & Elias, 2019; Shirzaei et al., 2021; Bundy et al., 2022).

The remainder of this study is organized as follows. Section 1.2 provides background information on flood risk management, PES programs, and the federal crop insurance program. Section 1.3 introduces the theoretical framework that derives the underlying channels through which the introduction of PES programs can affect flood damage on cropland. Section 1.4 presents the data and explores the spatial and temporal variation in the introduction of CREP and flood damage on cropland. Section 1.5 outlines the empirical framework, focusing on the identification strategy that reveals the flood mitigation benefits of CREP. Section 1.6 to 1.7 discuss the empirical findings, followed by falsification tests, sensitivity checks, and heterogeneity analysis. Section 1.8 concludes with a summary of the findings and policy suggestions.

1.2 Background and Institutional Context

1.2.1 Flood Risk Management: Gray and Green Infrastructure

Flooding is one of the most devastating natural disasters, with global economic losses exceeding $1.6 trillion since 2000, making it the second costliest peril after tropical cyclones (Aon, 2023). In the United States, annualized flood losses are estimated to be $32.1 billion under climate

conditions in 2020 and are projected to rise to $40.6 billion by 2050 under RCP4.5 scenario (Wing et al., 2022). The Mississippi River Basin has experienced an increasing frequency of major floods, including destructive flood events in 1927, 1969, 1979, 1982, 1993, 2005, 2011, and 2019.[1] For example, the 1993 flood in the upper Mississippi River Basin inundated over 6.6 million acres across 419 counties in the Midwest, resulting in estimated damages of $12 billion to $16 billion, with agriculture accounting for over half of these costs (Galloway, 1995). Most recently, in 2019, floods in the Mississippi River Basin prevented 20 million acres of crops from being planted, leading to approximately a $9 billion loss in crop sales along with additional insurance indemnity payouts (English et al., 2021). These events underscore the importance of effectively managing flood risks in the era of climate change.

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

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

1.2.2 Payments for Ecosystem Services Program

The voluntary restoration of those natural infrastructures has been limited due to several reasons (see Prokopy et al. (2019) for a review). First, landowners may be less aware of the private benefits of conservation because existing empirical evidence has been focused on off-site public environmental benefits, rather than on-site private benefits. Second, landowners bear upfront costs to adopt conservation practices while the private benefits, such as stream bank protection and flood mitigation, are often uncertain and realized over a long-term period. Lastly, the heavily subsidized crop insurance program in the U.S. reduces the private costs associated with production risks, potentially discouraging insured farmers from implementing long-term loss mitigation strategies (Di Falco et al., 2014; Annan & Schlenker, 2015; Claassen et al., 2017; Connor et al., 2021).

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

Financial incentives within PES programs typically involve an upfront payment to support the installation of conservation practices, as well as a series of annual payments to compensate for the

maintenance and opportunity costs associated with practice adoption. Although participants have the option to terminate the signed contract and remove the installed practices before the contract expiration date, premature contract termination usually incurs a non-completion penalty, which often involves repayment of all or a portion of the payments received up to the time of termination.

1.2.3 Conservation Reserve Enhancement Program

CREP is administered by the USDA's FSA in collaboration with the USDA's Natural Resources Conservation Service (NRCS) and is funded by the Commodity Credit Corporation (CCC) through partnerships with local, state, and federal governments. The primary objective of CREP is to incentivize farmers and landowners to convert agricultural land into conservation cover to address environmental and resource concerns at the state, regional, and national levels. For example, CREP in the Mississippi River Basin aims to restore filter strips, riparian buffers, and wetlands in the major tributaries of Mississippi River (e.g., IA, IL, MN, and OH) to reduce agricultural nonpoint source water pollution in the Gulf of Mexico and restore wildlife habitats. Since 1998, CREP has been introduced to selected groups of counties in 32 states. In the fiscal year of 2022, CREP allocated $154 million in annual payments to establish and maintain approximately 800,000 acres of conservation practices on agricultural land (USDA-FSA, 2023).

The introduction of CREP to a specific county or watershed requires collaboration between the partners (local and state government) and the federal government. The partners or the federal government first identify the environmental and resource concerns that can be addressed through the implementation of CREP. The federal agency then reviews and evaluates proposed conservation practices supported by CREP and their impacts on the local community in accordance with the requirements of the National Environmental Policy Act. The partners typically share at

least 30 percent of the program costs, which can be in the form of cash, in-kind contributions, or technical assistance.

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

Financial incentives in CREP include both one-time upfront payment and fixed annual payments throughout the contract lifetime. CREP offers cost-share assistance that covers 50 to 100 percent of the installation costs and fixed annual payments to compensate for the land rental rate and the maintenance costs of the installed practices. These annual program payments are designed to be competitive, typically ranging from 150 to 300 percent of the county's soil rental rate in the year of program participation, which is published by USDA's National Agricultural Statistics Service. The annual payment is further adjusted within counties based on soil types and productivity, using the national commodity crop productivity index published by the USDA's NRCS. Some states also offer additional upfront signing incentive payments to further incentivize landowners to adopt conservation practices.

Because the provision of ecosystem services often depends on the growth of vegetation over time, CREP contracts typically last 10 to 15 years, with options to maintain the installed practices beyond the contract's expiration date in return for additional payments. Participants have the option to terminate their contracts before the expiration date and remove the installed conservation practices. In such cases, they are obligated to repay the total payment they have received up until the termination date, along with applicable interest, as penalties for failing to complete the contract. Overall, CREP offers competitive payments and enforces strict non-compliance penalties, which contributes to the change in regional landscape over the medium to long term as the program becomes available to landowners.

Previous research indicates that farmers and landowners may have adopted conservation practices even without the financial incentives provided by the PES program, suggesting imperfect additionality (Chambers, 1992; Wu & Babcock, 1996; Ferraro & Simpson, 2002; Ferraro, 2008; Lichtenberg & Smith-Ramirez, 2011; Mezzatesta et al., 2013; Fleming, 2017; Fleming et al., 2018; Lichtenberg, 2021). In such instances, the introduction of PES programs may not lead to an overall increase in the adoption of conservation practices. However, the additionality of U.S. federal PES programs tends to be higher for land use conversion practices, such as the restoration of riparian buffers and filter strips in CRP (96-98 percent), compared to working land practices, such as conservation tillage in EQIP (47 percent) (Claassen et al., 2018).

1.2.4 Crop Loss Covered under the Federal Crop Insurance Program

In addition to the agri-environmental programs, the federal government also heavily subsidizes crop insurance program to help farmers manage risks associated with crop yield and revenue losses caused by weather and market conditions, such as drought, flood, and decline in crop price. In the

event of yield or revenue losses covered by the insurance plan, farmers receive indemnity payments as monetary compensation. These payments are calculated based on the difference between guaranteed and actual (realized) yield or revenue. Most crop insurance plans establish either guaranteed yield or revenue by using approved Actual Production History, which reflects the production potential using actual average per-acre yield of the insured's cropland for the past four to ten consecutive years (Rosch, 2021).

For yield protection, the guaranteed yield is determined by multiplying the Actual Production History by the selected coverage level, which can range from 50 to 85 percent with increments of 5 percent. An indemnity payment is triggered when the actual yield falls below the guaranteed yield. The indemnity payment covers the difference in yield multiplied by the selected percentage of the projected and harvest prices obtained from the futures market. In the case of revenue protection, the guaranteed revenue is calculated by multiplying the Actual Production History, coverage level of yield, and the greater of either the projected or harvest price. An indemnity payment is triggered when the actual revenue with harvest price falls below the guaranteed revenue, and the payment compensates for the difference in revenue.

The percentage of insured U.S. cropland has constantly increased from less than 30 percent in 1989 to approximately 70 percent in 1995 and then to nearly 90 percent (299 million acres) in 2015 (Farrin et al., 2016; Rosch, 2021). On average, from 2000 to 2021, 82 percent of eligible acres of row crops, such as corn, soybeans, wheat, cotton, rice, sorghum, and others, were enrolled in the federal crop insurance program.[2] The coverage level of insurance, the ratio of insured liability to total potential liability, has also increased over time, reaching 74 percent by 2021. The Federal Crop Insurance Corporation provides subsidies for crop insurance premiums, ranging from

[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/.

38 to 80 percent, depending on the contract terms, such as crop type, the coverage level, and an insurance unit to which the coverage level is applied to.

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

1.3 Theoretical Framework

I present a theoretical framework that illustrates how the introduction of a PES program can enhance climate change adaptation in agriculture by promoting the adoption of conservation practices. The framework employs a static model to describe how a risk-averse farmer maximizes expected utility by (i) allocating land use between crop production and conservation and (ii) adjusting the coverage level of crop insurance for the cropland in production. Subsequently, the model describes how the PES program's payment for conservation alters the farmer's optimal land use allocation. The framework highlights two key channels through which the PES program payment can mitigate crop losses: (i) by removing at-risk cropland from production for conservation, thus eliminating potential crop losses, and (ii) by reducing the extent of damage on

the remaining cropland in production through the protective services provided by established natural infrastructure. Finally, the framework suggests that the introduction of PES programs generates financial spillover effects on the crop insurance program by reducing disaster payouts.

1.3.1 Farmer's Land Use Decision

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

The farmer can choose to devote some of that cropland to conservation cover at a per-acre cost c. In doing so, the farmer obtains private benefits w that include erosion protection, recreational and scenic amenities, satisfaction from stewardship, along with per-acre monetary compensation

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

$r > 0$ from a PES program. These private benefits of conservation $w + r$ remain constant regardless of the states of nature (e.g., weather conditions). In addition, the conservation acreage e mitigates the extent of loss D on the remaining cropland $L - e$ under the bad state with a diminishing effect, $\frac{\partial D}{\partial e} \equiv D_e < 0$ and $\frac{\partial^2 D}{\partial e^2} \equiv D_{ee} > 0$.

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

$$\max_{e,\beta} V \equiv qU(\pi_1) + (1-q)U(\pi_0), \tag{1.1}$$

where:

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

and:

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

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

$$\frac{\partial V}{\partial \beta} \equiv qD(L-e)U'(\pi_1) \leq mqD(L-e)[qU'(\pi_1) + (1-q)U'(\pi_0)]. \tag{1.2}$$

Given that $U'(\cdot) > 0$, $U''(\cdot) < 0$, and $U'(\pi_1) > U'(\pi_0)$, the farmer would increase insurance coverage on crop loss as long as the marginal utility gained from higher indemnity payouts under the bad state on the left-hand side outweighs that from higher premium costs in both states on the right-hand side. If the premium is actuarially fair or subsidized ($m \leq 1$), then the farmer would fully insure crop loss under the bad state ($\beta = 1$) at any conservation acreage e because the marginal utility of income under the bad state always outweighs that under the good state for all e (i.e., $U'(\pi_1) \geq m[qU'(\pi_1) + (1-q)U'(\pi_0)]\ \forall e$). In fact, the federal crop insurance program

heavily subsidizes crop insurance ($m < 1$), so full insurance would be optimal for the farmer. However, the federal crop insurance program imposes restrictions on loss coverage, capping it at less than full insurance ($\beta < 1$). Thus, the farmer's optimal coverage level β^* is fixed at the maximum attainable level allowed by the program at any conservation acreage e.

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

$$\frac{\partial V}{\partial e} \equiv [qU'(\pi_1) + (1-q)U'(\pi_0)] \left\{ \begin{array}{c} \underbrace{-(y - mq\beta^* D)}_{\text{foregone net crop return and insurance premium}} \\ + \underbrace{w + r - c}_{\text{net return from conservation}} \\ \underbrace{- mq\beta^* D_e (L - e)}_{\text{reduced insurance premium for remaining cropland}} \end{array} \right\} \qquad (1.3)$$

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

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

1.3.2 Establishing Natural Infrastructure Through PES Programs

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

$$\frac{\partial e^*}{\partial r} \equiv -\frac{\frac{\partial^2 V}{\partial e \, \partial r}}{\frac{\partial^2 V}{\partial e^2}} \geq 0. \qquad (1.4a)$$

because

$$\frac{\partial^2 V}{\partial e\,\partial r} \equiv -\phi \underbrace{\left[qU'(\pi_1)\frac{\partial \pi_1}{\partial e} + (1-q)U'(\pi_0)\frac{\partial \pi_0}{\partial e}\right]}_{=0\ (\text{first-order condition for } e)} e^* + qU'(\pi_1) + (1-q)U'(\pi_0) \geq 0, \quad (1.4b)$$

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

$$\frac{\partial^2 V}{\partial e^2} \equiv q\left[U''(\pi_1)\left(\frac{\partial \pi_1}{\partial e}\right)^2 + U'(\pi_1)\frac{\partial^2 \pi_1}{\partial e^2}\right] + (1-q)\left[U''(\pi_0)\left(\frac{\partial \pi_0}{\partial e}\right)^2 + U'(\pi_0)\frac{\partial^2 \pi_0}{\partial e^2}\right] \leq 0, (1.4c)$$

because:

$$\frac{\partial^2 \pi_1}{\partial e^2} \equiv [-(1-\beta)D_{ee} - m\beta q D_{ee}](L-e^*) - 2[-(1-\beta)D_e - m\beta q D_e] \leq 0, \quad (1.4d)$$

and:

$$\frac{\partial^2 \pi_0}{\partial e^2} \equiv -m\beta q D_{ee}(L-e^*) + 2m\beta q D_e \leq 0. \quad (1.4e)$$

1.3.3 Loss Mitigating Benefits of PES programs

Now, I show that the PES program payment r mitigates the expected crop loss, $qD(e^*)(L-e^*)$, via two channels:

$$\frac{\partial qD(e^*)(L-e^*)}{\partial r} \equiv \frac{\partial e^*}{\partial r}\left[\underbrace{-qD(e^*)}_{\text{conversion effect}} + \underbrace{qD_e(L-e^*)}_{\text{protection effect}}\right] \leq 0, \quad (1.5)$$

because $\frac{\partial e^*}{\partial r} \geq 0$ as shown above and $D_e < 0$. Condition (1.5) reveals two potential channels through which the introduction of PES programs reduces crop loss. First, the PES program eliminates the risk of potential crop loss $qD(e^*)$ by converting at-risk cropland into a conservation use (the conversion effect). Second, the PES program reduces the extent of potential loss on the

remaining cropland in production through the established conservation practices $qD_e(L - e^*)$ (the protection effect).

Furthermore, given that the crop insurance policy covers β^* portion of crop loss, the loss mitigating benefits of PES programs lead to reduced insurance indemnity payouts. Thus, I have:

Proposition. *The introduction of PES programs reduces insurance indemnity payouts from the crop insurance program by establishing natural infrastructure that mitigates crop loss.*

1.4 Data

To estimate the flood mitigation benefits of CREP, I use administrative records from the USDA's RMA and FSA and construct county-by-year panel data on (i) flooded crop loss covered under the federal crop insurance program and (ii) the availability of CREP, acres enrolled, and program payments from 1989 to 2022. My analysis focuses on (i) 250 counties where CREP was introduced between 1998 and 2011 and (ii) 150 counties where CREP was never available until 2022. These counties are distributed across 13 states within two farm resource regions in the Mississippi River Basin: Heartland and Mississippi River Portal regions.[4] These regions are characterized by extensive crop production in the presence of flood risk because of their proximity to major tributaries of the Mississippi River, such as the Missouri River, Ohio River, and Arkansas River. The analysis only includes counties with crop acres insured under the federal crop insurance program before the introduction of CREP.

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

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

In the following subsections, I provide detailed information about the county-level panel data on CREP availability and participation (Section 4.1), flooded crop loss covered under the federal crop insurance program (Section 4.2), and weather information used in estimating the program effect (Section 4.3). Table 1.1 presents the average values of variables used in the main analysis for counties where CREP was introduced in any year after 1997 and counties where CREP was not available until 2022. Table A1 in Appendix A presents a comprehensive set of summary statistics.

1.4.1 Conservation Reserve Enhancement Program

The USDA's FSA provides county-by-year panel data on CREP availability and participation from 1998, the first year of CREP, to 2022. CREP became available in a county when landowners have the opportunity to receive payments from the program in return for establishing or maintaining

Table 1.1 Descriptive Statistics: Main Analysis

Time Period	**Year 1989-1997**		**Year 1998-2022**	
County: CREP introduction in any year post-1997	Yes	No	Yes	No
Crop Loss Experience	Average			
Indemnity payouts per flooded crop acre ($/acre in 2022$)	60.9	57.1	80.2	99.6
Indemnity payout ($1,000s in 2022$)	50.5	72.8	79.8	193.2
Crop acres flooded	375.8	469.6	338.2	666.6
Federal Crop Insurance Program Participation				
Crop acres insured (1,000s)	108.2	85.2	185.7	155.7
Coverage level insured (%, area-weighted)	64.4	63.8	73.9	70.7
Conservation Reserve Enhance Program (CREP)				
Number of acres enrolled	N/A	N/A	974.6	N/A
Annual program payments ($1,000s in 2022$)	N/A	N/A	201.0	N/A
Weather Conditions (1989-2019 only)				
Total Precipitation (mm)				
Post-harvest, Oct.-Mar.	355.6	449.1	359.9	437.4
Growing season, Apr.-Sept.	632.0	661.7	630.2	652.8
Growing degree days (10-29 Celsius)				
Post-harvest, Oct.-Mar.	193.5	277.7	216.9	302.8
Growing season, Apr.-Sept.	1,627.4	1,798.8	1,735.9	1,907.2
Number of counties	250	150	250	150
Number of observation (county-by-year)	2,250	1,350	6,250	3,750

Note: The table presents average values of variables used in the main analysis for 250 counties that introduced CREP between 1998 and 2011 and 150 counties that have never introduced CREP during the analysis period.
Source: USDA Risk Management Agency and Farm Service Agency, and Schlenker and Roberts (2009).

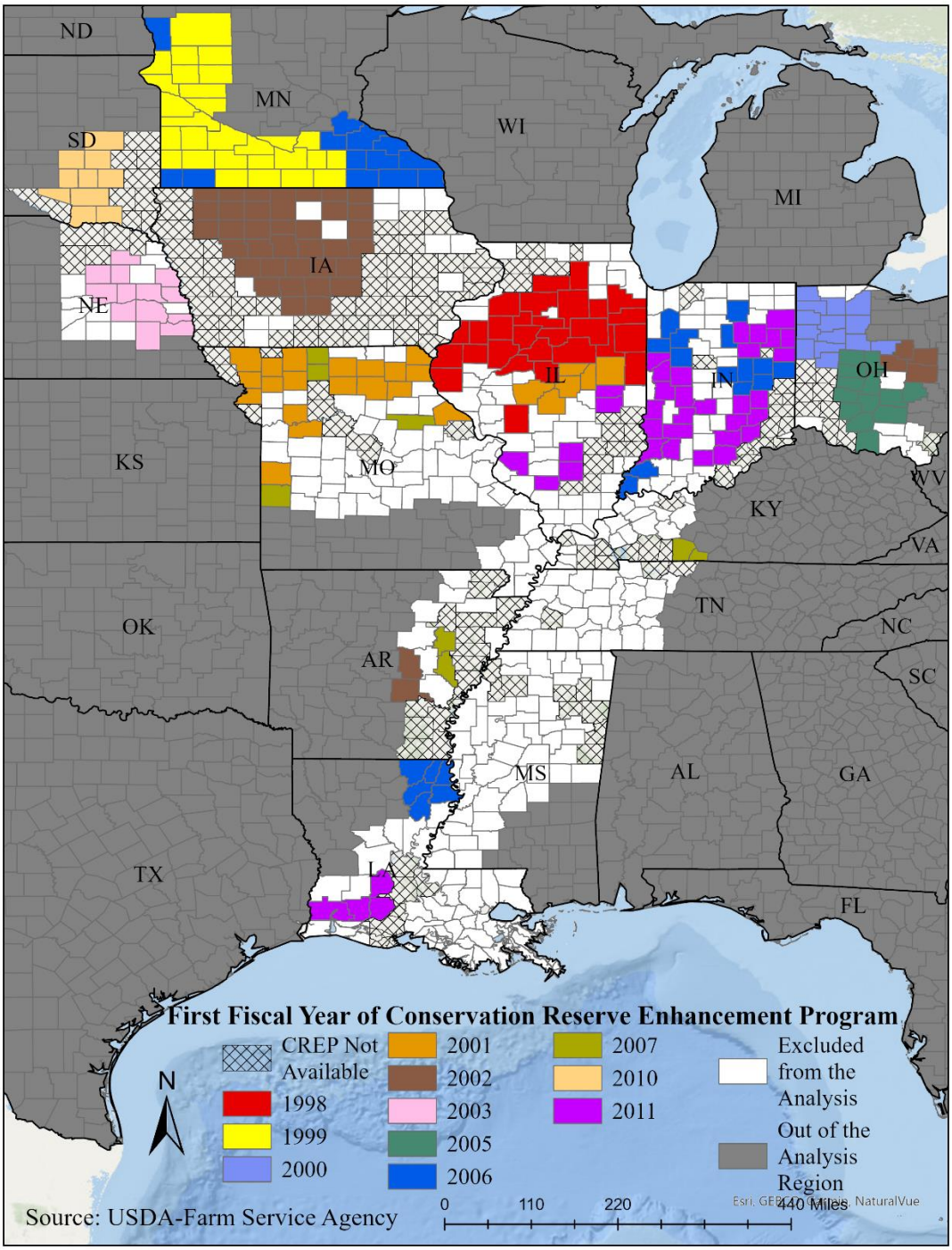
conservation practices. The county participates in CREP when landowners choose to enroll their land in the program and commit to adopting and maintaining conservation practices as specified in their CREP contract. Thus, the first year of CREP introduction may differ from the year of

participation, as landowners may not enroll any acres as soon as the program becomes available. The analysis follows the fiscal year cycle of annual CREP data. For instance, the fiscal year 1998 encompasses the period from October 1997 to September 1998. If CREP is introduced in the fiscal year of 1998, the conservation practices installed through CREP may provide protection services to neighboring cropland starting in the subsequent crop year of 1998. Therefore, I match crop loss data in crop year of 1998 with CREP data in the fiscal year of 1998 to construct the county-by-year panel data set.

The data set consists of (i) 250 counties where CREP was introduced between 1998 and 2011 and had insured crop acres between 1989 and the year of CREP introduction, and (ii) 150 counties where CREP was never available until 2022 and had insured crop acres between 1989 and 2011. Figure 1.1 presents a map that summarizes spatial and temporal variation in the timing of CREP availability across counties included in the analysis. CREP availability varies spatially and temporally even within the same state as the partnership may prioritize a specific watershed region to address environmental concerns and then subsequently expand the program to other regions with similar or different environmental and resource concerns. For instance, in 2005 (FY 2006) the Indiana State Department of Agriculture partnered with USDA's FSA and introduced CREP to counties in three watersheds to reduce agricultural nonpoint source pollution and restore wildlife habitats through the restoration of riparian buffers and wetlands. In 2010 (FY 2011), Indiana expanded CREP to counties located in eight other watersheds in the state with similar environmental concerns.

CREP participation varies spatially and temporally across counties, even if the timing of CREP introduction is the same. For instance, the opportunity costs of program enrollment, such as foregone crop return of program eligible agricultural land, may vary across farms and crop year.

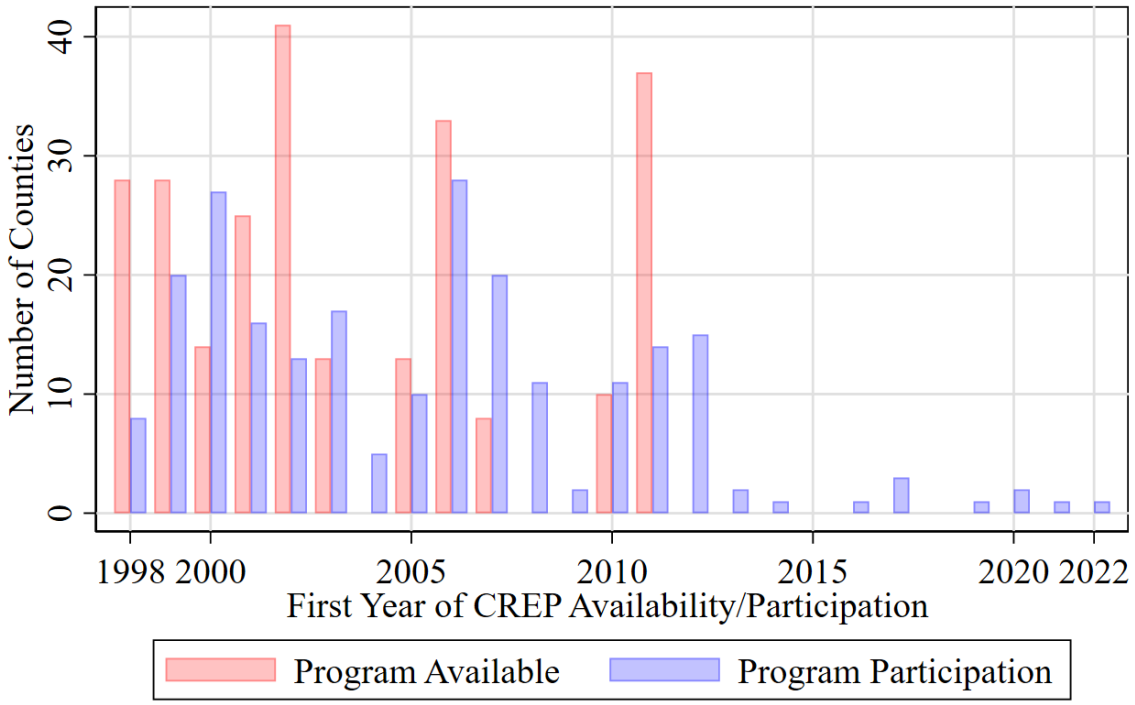
Figure 1.1 Spatial and Temporal Variation in the Introduction of CREP: Heartland and Mississippi River Portal Regions



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

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;

Figure 1.2 Conservation Reserve Enhancement Program: Timing Variation of Introduction and Participation across Counties, 1998-2022



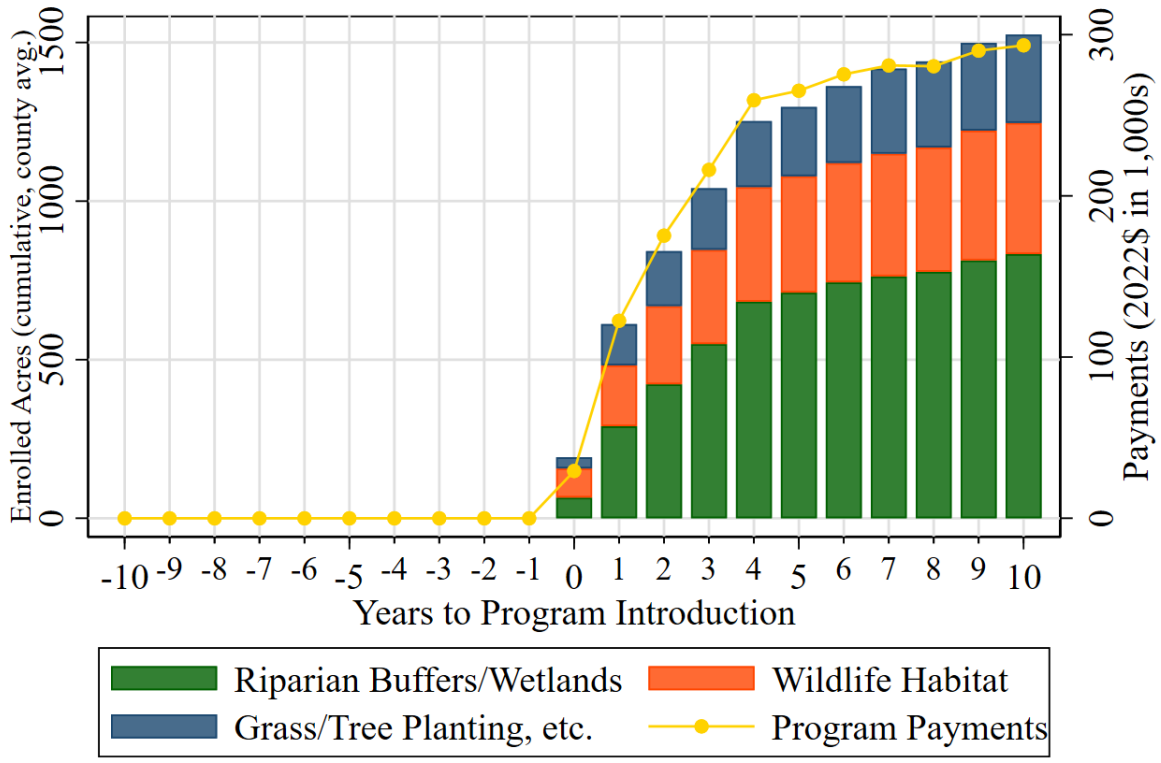
Note: The graph shows the number of counties that introduced Conservation Reserve Enhancement Program (CREP) in any year before 2012 (y-axis) by the initial fiscal year of CREP availability (red) or participation (blue) (x-axis). Among 400 counties included in the analysis, the CREP has become available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

Lichtenberg, 2004, 2007; Prokopy et al., 2019). Figure 1.2 provides an overview of timing variation in the CREP availability and participation across counties included in the analysis.[5]

[5] See Table A2 in Appendix A for a more detailed breakdown of the number of counties by state and their CREP availability and participation.

Figure 1.3 presents an overview of the county-level average acreage enrolled in CREP by practice type and the program payments in 250 counties with CREP by the duration of program availability. During the initial 11 years of the CREP implementation, the government invested a total of $622 million (in 2022$, CPI-adjusted) to establish and maintain approximately 380,000

Figure 1.3 Conservation Reserve Enhancement Program: Enrolled Acres and Program Spending by Event Time



Program Acre: Mean = 1135, SD = 2309
Program Payment (2022$ in 1,000s): Mean = 226, SD = 499

Note: The graph shows the average number of acres enrolled in the Conservation Reserve Enhancement Program (CREP) at the county level (y-axis left), as well as the corresponding payments made (y-axis right, in 2022$), for 250 counties with CREP availability in Heartland and Mississippi River Portal regions. The x-axis represents the length of exposure to the program availability (event time). *Source*: USDA Farm Service Agency.

acres of conservation practices. Types of conservation practices installed are consistent with two main objectives of the CREP in the Mississippi River Basin: (i) reduction of agricultural nonpoint source water pollution in the Gulf of Mexico and (ii) preservation of wildlife habitats. Roughly 50 percent of total acres of conservation practices installed through CREP are riparian buffers,

wetlands, and filter strips. Likewise, the restoration of wildlife habitats via vegetative buffers and conservation cover along the water bodies also accounts for 32 percent of total enrolled acres. The remainder of the conservation practices installed includes grass and tree plantings. According to the USDA's NRCS Conservation Practice Physical Effects and scientific literature, these conservation practices directly and indirectly mitigate flood risk on neighboring cropland by enhancing streambanks and addressing seasonal high water, ponding, and flooding (Darby, 1999; Acreman & Holden, 2013; Mason-McLean, 2020).

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

In the setting of staggered policy rollout, a panel data set that is balanced in calendar time becomes unbalanced in event time (duration after the policy onset) due to variation in the timing of policy adoption across counties. Thus, the estimated program effect across event time may vary simply due to changes in the composition of treated counties. To address this concern, the analysis focuses on counties with at least 11 years of exposure to the program availability, including the

year of program introduction. Out of 709 counties within the analysis region, eleven counties in Mississippi are dropped because CREP first became available in these counties in 2016.

1.4.2 Flood Damage on Cropland

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

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

available counties may be attributed to lower adoption rates of crop insurance compared to comparison counties, overstating the program's benefits.

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

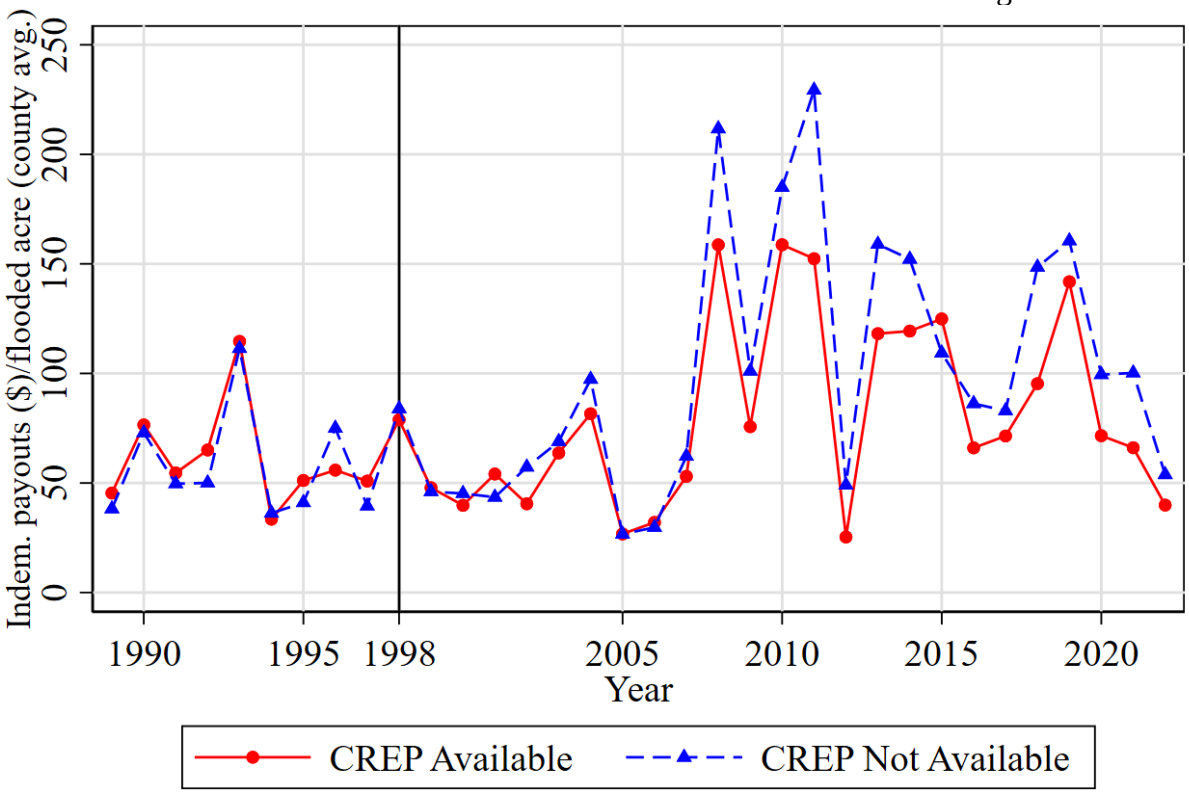
I find divergence in the trends of flood damage on cropland between counties with and without CREP availability after the first program introduction in the analysis region in 1998 (Figure 1.4). This observed divergence, however, may not necessarily be attributed to the introduction of CREP in the presence of unobserved heterogeneity and time-varying confounding factors, such as potential divergence in weather conditions and crop insurance adoption. Flooded crop losses are large in the years of major flood events in the Mississippi River Basin such as the years of 2008, 2011, 2014, and 2019. On the other hand, flooded crop losses are small in the year of severe drought such as 2012. Overall, flooded crop loss covered under the federal crop insurance program has increased due to weather anomalies combined with increasing crop insurance adoption (e.g., coverage level). Flood damage on cropland also varies spatially depending on geographical

conditions, hydrological networks, and weather conditions. Figure A1 in Appendix A presents a map that shows spatial heterogeneity of flood damage on cropland across counties before CREP became available in the region of analysis in 1998.

1.4.3 Weather

Climate conditions during the post-harvest (October to March) and growing seasons (April to September) affect future crop insurance decision and crop productivity (Moore & Huang, 2019). To ensure that counties with CREP and the comparison group share similar climate conditions, I

Figure 1.4 Trends in Flooded Crop Loss in the Federal Crop Insurance Program, 1998-2022: Counties with versus without Conservation Reserve Enhancement Program



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

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

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

1.5. Empirical Framework

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

1.5.1 Estimands of Interest

Suppose that I observe an annual crop loss for $i = 1, \dots, N$ counties over $t = 1, \dots, T$ years with variation in the timing of program introduction across counties ($N = 400$ and $T = 34$). Let T_i denote the first program-available year in a county i (i.e., the first year of the county being

"treated"), assuming $T_1 \leq T_2 \leq \cdots \leq T_N$ without loss of generality. Let $j = 1, \ldots, J$ denote the treated counties where CREP was eventually available by year T ($J = 250$). Let N_0 denote the number of counties where CREP was not available during the analysis period ($N_0 = 150$) with $T_i = \infty$ denoting that the county is never treated, then $J = N - N_0$. Using the potential outcomes framework (Rubin, 1974), let Y_{it} denote the observed crop loss in county i in year t and $Y_{it}(s)$ denote the potential outcome when CREP first becomes available in county i in year $s = 1, \ldots, T, \infty$. Under no policy anticipation effect and stable unit treatment value assumption (SUTVA), the observed crop loss outcome is then $Y_{it} = \mathbb{1}\{t < T_i\}Y_{it}(\infty) + \mathbb{1}\{t \geq T_i\}Y_{it}(T_i)$ where $Y_{it}(s) = Y_{it}(\infty)$ for $t < s$.

I expect that the loss mitigating benefits of CREP would generally increase with the duration of program availability (event time) for two reasons: (i) the gradual rise in program participation to establish conservation practices and (ii) the improved effectiveness of established conservation practices as vegetation on riparian buffers and wetlands matures. Let event time $k \leq K$ denote the year relative to the first year of program availability T_j ($k = t - T_j$). Then, the evolution of crop loss experience in county j treated in year T_j across event time k, relative to its average crop loss during L_j ($L_j \leq T_j - 1$) pre-policy periods (i.e., the trajectory of treated outcome) is:

$$\dot{Y}_{jT_j+k}(T_j) \equiv Y_{jT_j+k}(T_j) - \frac{1}{L_j}\sum_{l=1}^{L_j} Y_{jT_j-l}\,. \tag{1.6}$$

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

A county-specific program effect at event time k for each county j treated in year T_j is then the divergence in the two trajectories of crop loss:

$$\tau_{jk} = \dot{Y}_{jT_j+k}(T_j) - \dot{Y}_{jT_j+k}(\infty), \tag{1.7}$$

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

$$ATT_k \equiv \frac{1}{J}\sum_{j=1}^{J} \tau_{jk} = \frac{1}{J}\sum_{j=1}^{J} \left[\dot{Y}_{jT_j+k}(T_j) - \dot{Y}_{jT_j+k}(\infty)\right]. \tag{1.8}$$

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

$$ATT \equiv \frac{1}{K+1}\sum_{k=0}^{K} \frac{1}{J}\sum_{j=1}^{J} \tau_{jk}\,. \tag{1.9}$$

1.5.2 Identification Strategy

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

differential changes in flooded crop losses over time, we can estimate the loss mitigating benefits attributable to CREP.

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

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

estimated by the staggered DID estimator proposed by Callaway and Sant'Anna (2021) to examine the robustness of the findings.

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

The estimated average program effect across event time, $\widehat{ATT}_k$ is obtained by taking the simple average of the estimated county-specific program effect $\hat{\tau}_{jk}$ (equation (1.8)). This program effect estimator takes the form of a weighted DID estimator, where the weights for untreated counties are chosen to maximize the similarity between the synthetic control counties and the treated counties in terms of both *individual* and *average* pre-policy trends in crop loss. Key identification assumptions include the absence of time-varying confounding factors, policy anticipation effects, and spillover effects. This estimator also addresses bias arising from potential program effect heterogeneity and timing variation in program introduction.

Time-varying confounding factors pose a threat to identification because the divergence in post-policy crop loss between counties with CREP and those without CREP could be attributed to factors other than the introduction of CREP. For instance, a decrease in crop insurance adoption in CREP-available counties after the program introduction could decrease overall reported crop losses, thus overstating the program's effect. Similarly, a decrease in excessive precipitation in

CREP-available counties during the post-policy period could also overstate the program's effect. On the other hand, a decrease in the participation of other conservation programs that support similar conservation practices in CREP-available counties may underestimate the impact of CREP on crop loss. Although the assumption of no time-varying confounding factors is fundamentally untestable due to unobserved confounding factors that vary over time, I examine whether these observed time-varying confounding factors exhibit parallel trends before and after the policy to enhance the credibility of the estimated program effect.

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

The assumption of no policy anticipation effect is plausible because individual landowners may not be aware of future program availability. The availability of CREP in each county is primarily driven by the state and federal governments to address environmental quality concerns that extend across vast distances. Thus, individual landowners may not be aware of future program availability. In addition, landowners make conservation decisions for agricultural land, while tenant farmers make decisions on crop production and insurance, mitigating the potential

anticipation effect on crop insurance and cropping decisions of rented farms.[6] Finally, CREP has strict program eligibility criteria for cropland location, cropping history, and land characteristics, which exclude cropland with high risk of loss. Overall, farmers have little incentive to manipulate crop loss in anticipation of program introduction.

Suppose that conservation practices implemented through CREP effectively reduce flooded crop losses. The assumption of no spillover effects is plausible if the flood mitigation benefits of these practices diminish with increasing distance and primarily benefit the remaining cropland in the same farm. Spillover effects between counties, however, can bias the estimated program impact (a) downward if flood mitigating practices in upstream counties with CREP also reduce flood damage in downstream non-CREP counties that construct synthetic controls, or (b) upward if flood mitigating practices in upstream counties with CREP further reduce flood damage in downstream counties with CREP. However, unless the composition of a neighboring upstream county and the magnitude of spillover effects among neighboring counties are systematically associated with CREP availability, the estimated average program effect on flooded crop loss would not be significantly biased by spillover effects. In Section 1.7, I investigate whether the flood mitigation benefits vary with the number of neighboring counties with CREP.

1.5.3 Synthetic Control Method

To construct a comparison unit for each treated county, I employ the partially pooled SCM proposed by Ben-Michael et al. (2022) and construct a synthetic control for each treated county (Doudchenko & Imbens, 2016; Ferman & Pinto, 2021). To be specific, the partially pooled SCM

[6] 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).

allocates weights across untreated counties (including those not-yet treated[7]) to minimize the weighted average of two imbalance measures: (i) the average of difference in pre-policy trends in outcomes between the individual treated and synthetic control counties (individual fit) and (ii) the difference in average pre-policy trends in outcomes between the treated and synthetic control counties (pooled fit), where both fits are measured by root mean squared difference (see Appendix A for detailed weight allocation procedure).

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

$$\hat{\tau}_{jk} = \dot{Y}_{jT_j+k}(T_j) - \hat{\dot{Y}}_{jT_j+k}(\infty) \tag{1.10}$$

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

The estimated county-by-event time program effect $\hat{\tau}_{jk}$ can be aggregated to obtain the estimated average program effect across event time $\widehat{ATT}_k$ and the overall program effect $\widehat{ATT}$ using equations (1.8) and (1.9). For statistical inference, I use wild bootstrap to construct confidence intervals for the estimated ATT.[8]

In addition to pre-policy trends in flooded crop loss, I include average weather conditions during 1989-1997 as auxiliary covariates in choosing synthetic control weights. Historical weather conditions may capture additional information that explains future crop loss that cannot be fully explained by pre-policy trends in crop loss. For example, crop type, crop profitability, and farming

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

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

practices are likely to be similar across counties that have similar weather conditions in addition to similar experience in crop loss. Thus, synthetic control counties likely consist of qualitatively similar farms compared to the treated counties, except for the availability of CREP. As a robustness check, I also present the estimation result excluding auxiliary covariates in Section 6.4.

1.6 Results

I first show that synthetic controls for counties with CREP tend to consist of counties without CREP in the same state or neighboring states. Then, I present estimated flood mitigation benefits of CREP during the initial 11 years of program implementation, $\widehat{ATT}_k$ and $\widehat{ATT}$ in equations (1.8) and (9). I also compare pre- and post-policy trends in potential confounding factors and placebo outcome between counties with CREP and synthetic controls. Then, I conduct sensitivity analysis to discuss the robustness of the findings, including the estimation of program effect using other DID estimator. Next, I decompose the estimated overall flood mitigation benefits into two primary mechanisms discussed in the theoretical framework by combining the theoretical model with the estimated program effects, program data, and remotely sensed land cover data. Finally, I explore spatial and temporal heterogeneity of the flood mitigation benefits of CREP.

1.6.1 Flood Mitigation Benefits of CREP Introduction

I find that the constructed synthetic control counties consist of untreated counties that are geographically closer to the counties with CREP (Figure 1.5). For example, in Iowa, 35 counties with CREP have a total of 35 synthetic controls that primarily consist of untreated counties within the same state (63 percent) and a neighboring state, South Dakota (21 percent), on average. Each synthetic control county typically consists of 5 to 11 different untreated counties with an average

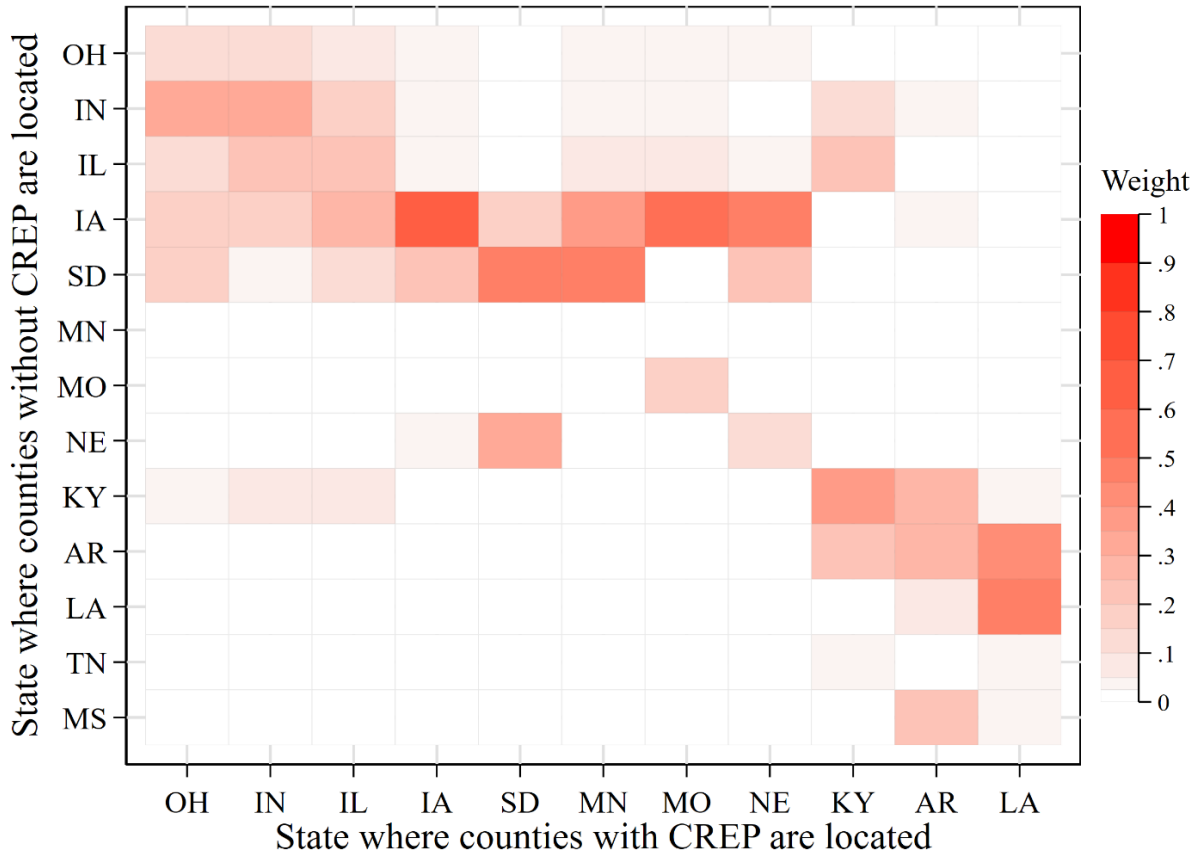
of 7.7 counties. Overall, the diagonal pattern in Figure 1.5 (excluding Tennessee and Mississippi that do not have counties with CREP) suggests that the post-policy average crop loss that counties with CREP would have experienced in the absence of the program is estimated based on the post-policy average crop loss in neighboring untreated counties that exhibit similar pre-policy trends in crop loss and production conditions.

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

I find economically and statistically significant flood mitigation benefits of conservation investments made through CREP (Figure 1.7). In the initial 11 years of CREP implementation, the estimated average reduction in annual indemnity payouts per acre loss is \$27.3/acre, which corresponds to a 26 percent decrease from the estimated counterfactual crop loss of \$106.4/acre, that is, the average post-policy outcome in synthetic control (\$108/acre) adjusted by the pre-policy difference in average outcome (-\$1.6/acre). The flood mitigation benefits generally increase with the duration of program availability. On average, the magnitude of reduction in indemnity payouts per flooded crop acre rises from \$17/acre during the first 5 years to \$35.8/acre after 6 to 11 years of program implementation (20 to 29 percent reduction relative to the estimated counterfactuals of \$83.5/acre and \$125.5/acre).

Compared to the same set of synthetic control counties, I also find that both total indemnity payouts and crop acres lost due to flooding (both numerator and denominator of the ratio outcome)

Figure 1.5 Spatial Distribution of Synthetic Control Weights Allocated to Untreated Counties



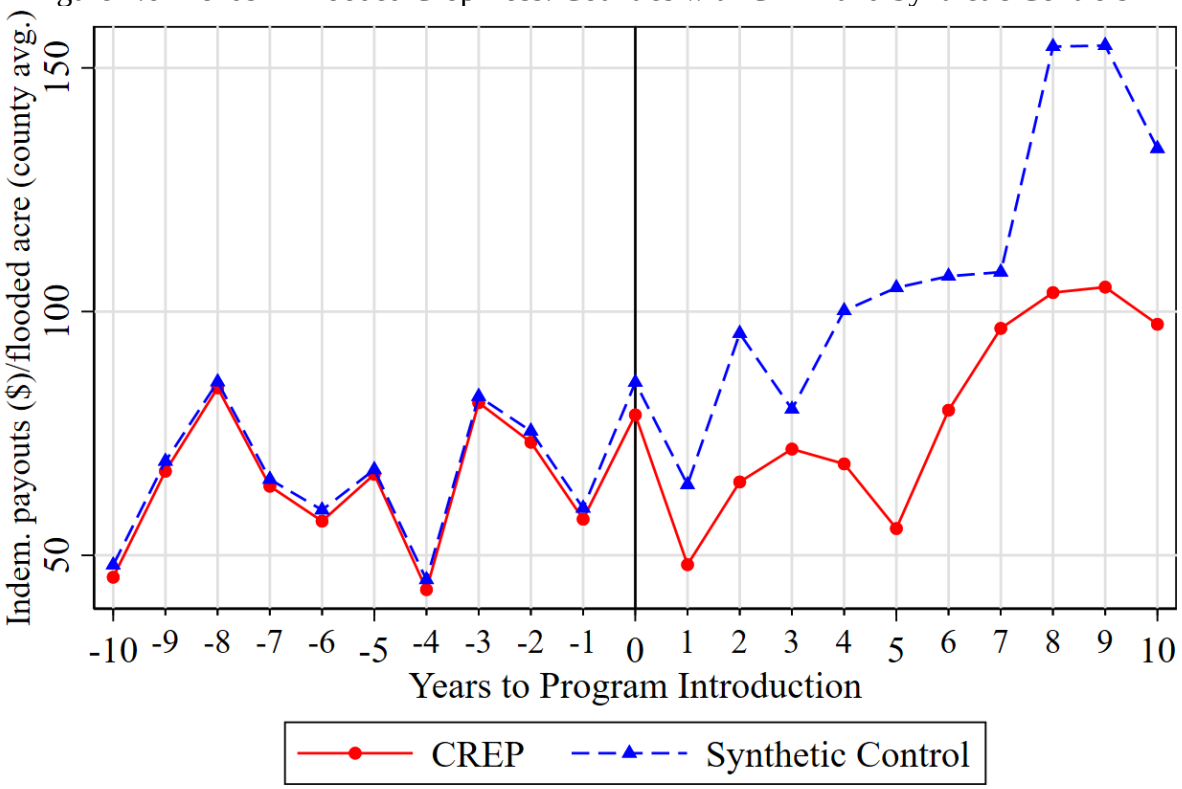
Note: The figure presents the distribution of weights assigned to counties without CREP in each state (y-axis) when constructing synthetic controls for counties with CREP in a given state (x-axis). When multiple counties in state a are treated, the sum of synthetic control weights for all treated counties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

in counties with CREP decreased after the introduction of CREP. During the pre-policy periods, the average annual indemnity payouts for flooded crop damage in counties with CREP are only $5,546 lower than that of synthetic control counties ($67,344 and $72,890; Figure A2 in Appendix A). The difference, however, increases to $107,587 during the post-policy periods ($90,406 and $197,993). Similarly, the average annual flooded crop acres in counties with CREP are only 14 acres fewer than those of the synthetic control counties during the pre-policy periods (399 and 413 acres; Figure A3), while the difference increases to 244 acres during the post-policy periods (360

and 604 acres). I calculate that the introduction of CREP led to an average reduction of 53 percent in total indemnity payouts and a 39 percent decrease in crop acres lost due to flooding, compared to the synthetic control's post-policy outcome adjusted by the pre-policy difference in outcome (589 acres and $192,447 of indemnity payouts).

To assess the overall reduction in flooded crop loss due to the introduction of CREP, I combine (a) the reduced indemnity payouts per flooded crop acres with (b) the avoided indemnity payouts resulting from the reduced number of flooded crop acres in counties with CREP. First, CREP reduced the extent of damage on 359.9 flooded crop acres by $27.3/acre during the post-policy period. Second, the reduced number of flooded crop acres is 229.6 acres (Figure A3) and the

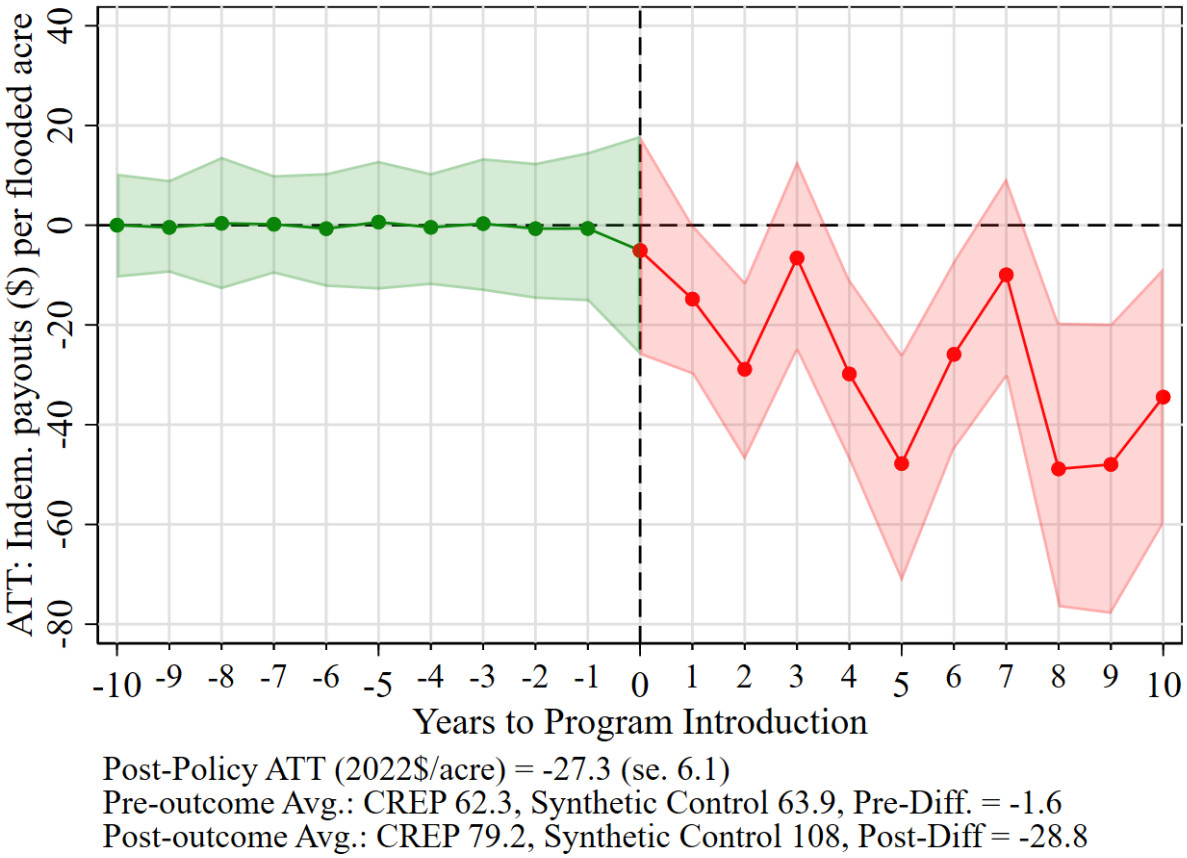
Figure 1.6 Trends in Flooded Crop Loss: Counties with CREP and Synthetic Controls



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

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

Figure 1.*7* Estimated Impact of CREP Introduction on Flooded Crop Loss



Note: The graph shows the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss (indemnity payouts per flooded crop acre in 2022$/acre, y-axis) across event time (x-axis) with 95 percent confidence intervals. The estimated average program effect is calculated by comparing the average change in crop loss relative to pre-policy average between 250 counties with CREP and their synthetic controls. In addition to lagged outcomes, total precipitation (mm) and growing degree days during the post-harvest (October to March) and crop growing seasons (April to September) are used as auxiliary covariates in choosing weights of untreated and not-yet treated counties to construct synthetic controls. Confidence intervals (95%) are constructed using wild bootstrap.

avoided indemnity payouts on those flooded acres are $106.4/acre (Figure 1.6). This calculation yields a total savings of $94 million in indemnity payouts that would have been paid to the insureds in the absence of CREP in 250 counties during the initial 11 years of program implementation.

To obtain the total avoided flood damage in terms of crop acreage, I take the ratio of $94 million in indemnity payouts to the estimated counterfactual post-policy average indemnity payouts in counties with CREP ($106.4/acre), which yields roughly 900,000 acres. Furthermore, combining the reduction in total indemnity payouts ($94 million) with the government's program

spending during the same period ($622 million), the financial spillover effects of introducing CREP to the federal crop insurance program equal a $151 reduction in insurance claims for flooding per $1,000 of CREP spending. Given that the indemnity payout only covers a portion of flood damage, I use the post-policy average of insurance coverage level in counties with CREP (73 percent) and calculate that the flood mitigation benefits of CREP introduction are $207 (=$151/0.73) per $1,000 of CREP spending.

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

The magnitude of flood mitigation benefits relative to program costs is noteworthy when compared to other social benefits of PES programs. On a national scale, the environmental benefits of CRP account for 70 to 85 percent of the program payments (0.70-0.85) although the benefit-cost ratio varies across regions (Hansen, 2007). Focusing on the Indian Creek watershed in Iowa, CRP's environmental benefits could potentially outweigh program payments by a factor ranging from 1.5 to 8.1 (Johnson et al., 2016). The environmental benefits in these studies include

improvements in soil, air, and water quality, wildlife habitats, and flood mitigation in residential areas. Other relevant studies find a benefit-cost ratio of 0.012 for groundwater benefits of CREP in Kansas that retires irrigation water rights (Manning et al., 2020), and a benefit-cost ratio of 2.31 for the crop yield benefits of wetland easement programs in the United States (Karwowski, 2022).

1.6.2 Confounding Factors

The key identification assumption of weighted DID estimators is the absence of time-varying confounding factors that may also cause the post-policy divergence in outcome other than the introduction of CREP, such as post-policy divergence in (i) crop insurance adoption, (ii) weather conditions, or (iii) conservation investments from other similar PES programs. Although the assumption of no time-varying confounding factor is fundamentally untestable due to unobserved confounding factors, I provide supportive evidence of the assumption by investigating whether important time-varying confounding factors have relatively parallel pre- and post-policy trends.

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

Second, the post-policy divergence in crop losses between counties with CREP and the synthetic control may be attributable to different weather conditions that affect flood risk such as excessive precipitation and temperature. I find that both total precipitation and growing degree

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

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

1.6.3 Placebo Test

I investigate whether a placebo outcome that should not be affected by conservation investments through CREP diverges after the introduction of CREP between counties with CREP and the synthetic control. The federal crop insurance program's revenue protection covers the insured's revenue loss due to a decline in crop price in the futures market (see Section 1.2.4 for details). Indemnity payouts resulting from a decrease in crop price, therefore, serve as a placebo outcome that should remain unaffected by the availability of CREP. Contrary to the post-policy divergence observed in indemnity payouts due to flooding between the two groups, I do not find post-policy divergence in payouts related to low crop price (Figure A10). This finding suggests that the comparison between counties with CREP and the synthetic control is expected to reveal

differences in outcomes that are specifically related to the availability of CREP, such as the reduction in flood damage on cropland induced by the establishment of natural infrastructure. In addition, this finding implies that the observed divergence in flood insurance claims between the two groups is unlikely to be driven by differences in loss reporting behavior or transaction costs associated with receiving insurance payouts between farmers in these groups.

1.6.4 Sensitivity Analysis

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

The findings are also not driven by a few counties with extreme program effects and are also robust to relaxed screening criteria for counties included in the analysis. First, the overall program effect is stable in magnitude even when excluding the top and bottom 1 or 5 percentile of county-by-event time program effects $\hat{\tau}_{jk}$ in equation (1.10), which yields \$28.4/acre and \$29.8/acre reduction in indemnity payouts per flooded crop acre compared to \$27.3/acre in baseline. Similarly, excluding counties with top and bottom 1 or 5 percentile of the estimated overall program effect yields similar \$26.7/acre and \$26.9/acre reductions in indemnity payouts per flooded crop acre. Finally, the findings remain consistent when expanding the analysis to 635 counties with any flood insurance claims on cropland during the pre-policy period. The estimated program effect remains at \$23.2/acre and is statistically significant (Figure A15).

Finally, the findings remain robust when implementing DID by the cohort of program introduction (Table A3). Using the same data set, I use the staggered DID estimator proposed by Callaway and Sant'Anna (2021) with untreated and not-yet treated counties as the control group. Without the inclusion of weather covariates, I observe pre-trends in flood damage between the comparison group and counties with CREP (Figure A16). The estimated post-policy ATT is an \$8.4/acre reduction in flood damage but is not statistically significant. The presence of pre-trends in flood damage may mask the true program effects in this case. When accounting for the same set of weather covariates, the pre-trends in flood damage persist with a reduced magnitude (Figure A17). However, the magnitude of the estimated post-policy ATT increases to a \$17.9/acre reduction in flood damage and is statistically significant. Thus, both the average of county-specific DIDs with SCM (Figure 1.7) and the weighted average of DIDs for each cohort of program adoption (Figure A17) deliver qualitatively similar findings that the introduction of CREP has

mitigated flood damage on cropland. Overall, the sensitivity analysis demonstrates the robustness of the findings.

1.6.5 Decomposing the Flood Mitigation Benefits: Conversion and Protection Effects

Section 1.3 outlined two primary mechanisms through which the introduction of PES program can influence flood damage on cropland: (i) the removal of at-risk cropland from production for conservation purposes (the conversion effect) and (ii) the reduced extent of damage on remaining cropland due to the established natural infrastructure (the protection effect). I use the theoretical framework to calculate the relative contributions of these two channels to the estimated overall loss mitigating benefits of CREP.

Let ΔQ and Δe denote the respective changes in total flood damage on cropland and established conservation acreage induced by the introduction of CREP during the post-policy period. Using equation (1.5) in Section 1.3.3, a linear approximation of the change in total flood damage ΔQ, measured by insurance claims with coverage level β, can be written as:

$$\underbrace{\beta \Delta Q}_{\text{reduced insurance claims}} \approx \left[\underbrace{-\beta q D}_{\text{conversion effect}} + \underbrace{\beta q D_e (L - e)}_{\text{protection effect}} \right] \underbrace{\Delta e}_{\text{additional conservation acreage}} . \quad (1.11)$$

By rearranging terms, I obtain:

$$\underbrace{\beta q D_e (L - e)}_{\text{protection effect}} \approx \underbrace{\frac{\beta \Delta Q}{\Delta e}}_{\text{reduced insurance claims per acre}} + \underbrace{-\beta q D}_{\text{conversion effect}} . \quad (1.12)$$

The relative contribution of protection effect can be approximated by the estimated overall reduction in flood insurance claims per acre enrolled in the program ($\beta \Delta Q / \Delta e$) less the avoided flood insurance claims per acre of cropland enrolled in CREP ($\beta q D$). Thus, to decompose the total effect, I approximate three components on the right-hand side of the equation (1.12).

Consider first the ratio in the denominator on the right-hand side, $\beta\Delta Q/\Delta e$. To obtain the total reduction in flood insurance claims ($\beta\Delta Q$), I use the estimated reduction in flood insurance claims in counties with CREP during the initial 11 years of program implementation (post-policy period), that is, \$94 million obtained in Section 6.1. The change in conservation acreage induced by CREP (Δe) equals the total crop acres enrolled in the program during the post-policy period, which amounts to 380,000 acres. The ratio of these two factors yields a \$247 reduction in total flood insurance claims per acre enrolled in CREP during the post-policy period, which is equivalent to a \$22.5 reduction in annual indemnity payouts per acre enrolled in CREP (= \$247/11 years).

Consider the conversion effect (βqD), that is, the avoided flood insurance claims per crop acre enrolled in the program due to the removal of cropland. The annual flood insurance claims that would have been made by crop acres enrolled in CREP is approximated by the average flood insurance claims in control group during the post-policy period, after adjusting for the pre-policy difference, which yields \$192,447 (= \$197,993 less \$5,546; Figure A2). Assuming that the flood insurance claims are made by crop acres located within floodplains,[9] I calculate the number of crop acres within floodplains by overlaying (i) a map of areas with a 1 percent annual chance of flooding (the 100-year floodplain or Special Flood Hazard Area) obtained from Woznicky et al. (2019) and (ii) maps of cropland from 1989 to 2021 obtained from the United States Geological Survey (USGS)'s Land Change Monitoring, Assessment, and Projection (LCMAP).[10] The post-policy average crop acres within floodplains in synthetic control counties (34,047 acres) less the pre-policy difference between CREP and control counties (10,006 acres) yields 24,041 acres that

[9] Using the total crop acres in the county as the denominator would understate the avoided flooded crop loss for cropland enrolled in CREP because the program explicitly targets cropland adjacent to water bodies.
[10] See Woznicky et al. (2019) for the detailed discussion on the model used to generate the floodplain map. The data and descriptions are available at: https://www.epa.gov/enviroatlas/forms/enviroatlas-data-download. The data and descriptions about the Primary Land Cover in LCMAP Conterminous United States (CONUS) Collection 1.3 are available at: https://www.usgs.gov/special-topics/lcmap/lcmap-data-access.

approximates the counterfactual cropland within floodplains in counties with CREP during the post-policy period. Taking the ratio of the two yields that the avoided annual flood insurance claims for cropland enrolled in CREP equal $8/acre (= $192,447/24,041 acres).

Finally, combining the two terms on the right-hand side of equation (1.12) reveals that the conversion effect amounts to $8 out of the total reduction of $22.5 in annual indemnity payouts due to flooding. This implies that the conversion effect contributes to approximately 35 percent of the estimated flood mitigation benefits of CREP, with the remaining 65 percent attributed to the protection effect during the initial 11 years of program implementation.

1.7 Program Effect Heterogeneity

The impact of PES programs on mitigating crop losses can vary across counties. To explore the program effect heterogeneity, I conduct a descriptive analysis to examine the linear relationship between the estimated county-level program effects across event time and county characteristics, including potentially endogenous factors such as the extent of program participation and crop insurance adoption. To be specific, I regress the estimated county-by-event time program effects on flooded crop loss, $\hat{\tau}_{jk}(0 \leq k \leq 10)$ in equation (1.10), on county-level characteristics and program data that could explain the differences in loss mitigating benefits. These characteristics include whether a county is located downstream of the Mississippi River Basin, the adoption of alternative risk management strategies such as levees and crop insurance, the overall resilience of the county to natural disasters, weather conditions, and the acreage enrolled in CREP. Table 1.2 provides a full list of county characteristics with summary statistics. In this analysis, I use 2,666 out of 2,750 estimated county-by-event time program effects from 250 counties with CREP for 11

years of post-policy period because county-level weather data are not available for the year 2020-2021. The results of the linear regression are presented in Table 1.3.

Table 1.2 Descriptive Statistics: Heterogeneity Analysis

Variables	Mean	SD	Min	Max
Estimated Program Effect $\hat{\tau}_{jk}$ $(0 \leq k \leq 10)$				
ATT: Indemnity payouts per flooded crop acre ($/acre in 2022$)	-28.5	123.1	-556.8	831.3
Conservation Reserve Enhance Program (CREP)				
Duration of CREP availability in years	4.9	3.1	0	10
Acreage enrolled	1158.2	2335.3	0	20197.2
Inter-County Spillover Effects				
Number of neighboring counties with CREP	4.7	1.6	1	9
Upstream versus Downstream (Heartland versus Mississippi River Portal)				
= 1 if a county is located in the Mississippi River Portal region (downstream)	0.05	0.23	0	1
Alternative Flood Mitigation Measure (Gray Infrastructure)				
Area protected by levees (acre, 1,000s)	18.2	80.4	0	670.2
Federal Crop Insurance Program Participation				
Coverage level insured (%, area-weighted)	73.0	6.1	50.5	86.5
Crop acres insured (1,000s)	184.8	91.3	12.7	559.2
Community Resilience to Natural Hazard				
FEMA Community Risk Factor	1.1	0.1	0.8	1.6
Weather during growing season (Apr-Sept) 1989-2019				
Total precipitation (mm)	623.6	152.9	235.1	1519.4
Total growing degree days (10-29 Celsius)	1722.5	292.9	1031.7	2848.7
Num. Observations (CREP county-by-post policy event time): 2,666 (250-by-11 less 84)				

Note: The table presents summary statistics of variables used in the analysis of program effect heterogeneity for 250 counties that introduced CREP by 2011. Out of 2750 estimated county-by-event time post-policy effects, 84 estimates in 2020 and 2021 are dropped due to unavailability of weather data.

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

Table 1.3 Program Effect Heterogeneity

Dep. Var.: ATT Indemnity payouts per flooded crop acre (in 2022$)	**Estimate (s.e.)**
A. Conservation Reserve Enhance Program (CREP)	
Duration of CREP availability in years	-2.04*
	(0.96)
Number of acres enrolled, standardized	-12.6***
	(3.28)
B. Inter-County Spillover Effects	
Number of neighboring counties with CREP availability, standardized	1.18
	(1.68)
C. Upstream versus Downstream (Heartland versus Mississippi River Portal)	
= 1 if a county is located downstream of the Mississippi River	-82.4***
	(22.3)
D. Alternative Flood Mitigation Measure (Gray Infrastructure)	
Area protected by levees, standardized	6.24
	(4.99)
E. Federal Crop Insurance Program Participation	
Coverage level insured (%, area-weighted), standardized	-13.9***
	(3.02)
Crop acres insured (1,000s), standardized	8.60**
	(2.96)
F. Community Resilience to Natural Hazard	
FEMA Community Risk Factor	-1.83
	(2.65)
G. Weather during growing season (Apr-Sept) 1989-2019	
Total precipitation (mm) Apr-Sept, standardized	15.7***
	(2.66)
Total Growing degree days (10-29 Celsius), standardized	16.2***
	(3.93)
Constant	-19.6*
	(9.63)
Outcome Mean: ATT Indemnity payouts per flooded crop acre (in 2022$)	-28.5
Num. Observations (CREP county-by-post policy event time)	2,666
R-squared	.052
F-statistics	14.96

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

1.7.1 Nature-based Infrastructure Established through CREP

A potential mechanism of the estimated loss mitigating benefits of the PES program availability is the establishment of conservation practices subsidized by the program. I use the cumulative acreage of conservation practices established through CREP to measure the extent of natural infrastructure established in each county after the program introduction.

I find that the magnitude of benefits increases with both the duration of exposure to the PES program and the cumulative acreage of conservation practices implemented through the program (Panel A of Table 1.3). This confirms that the estimated loss mitigating benefits are likely driven by the adoption of flood mitigation practices on agricultural land under CREP. The duration of program availability may also partially capture the maturity of vegetation on conservation practices installed through the program.

1.7.2 Inter-County Spillover Effects

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

I find that the extent of loss mitigating benefits varies little with the number of neighboring counties with CREP (Panel B of Table 1.3). This finding implies that the loss mitigating benefits of CREP introduction are primarily confined to the cropland within the county. The decomposition of flood mitigation benefits in Section 6.5 also suggests that the conversion effect accounts for 35 percent of the overall benefits, which may not generate spillover effects. On the other hand, if spillovers affect both CREP and non-CREP counties, they may offset each other, resulting in little variation in estimated flood mitigation benefits. In both scenarios, inter-county spillover effects would not significantly bias the estimated flood mitigation benefits.

1.7.3 Upstream versus Downstream Farm Resource Regions

Counties in the Mississippi River Portal region, located downstream of the Mississippi River Basin, may have higher flood risk compared to counties in the Heartland region, located upstream of the Basin. I find that the loss mitigating benefits are greater in the Mississippi River Portal region where the flood risk is inherently high (Panel C of Table 1.3). This indicates that the implementation of PES programs could be an effective production risk management strategy in downstream areas.

1.7.4 Presence of Infrastructure for Flood Mitigation

Levee construction along streams and rivers is an alternative flood risk mitigation measure in the Mississippi River Basin. If croplands are already protected from flood risk by levees, the establishment of conservation practices may have a smaller flood mitigation impact compared to areas without existing flood mitigation measures. To assess the interaction between protection services provided by green and gray infrastructures, I explore a linear association between the

magnitude of estimated loss mitigating benefits of CREP and the area of floodplain excluded from floodwater by levee systems, obtained from the U.S. Army Corps of Engineer's National Levee Database.[11]

I find suggestive evidence that the loss mitigating benefits could be greater in areas with little protection from flood by levees (Panel D of Table 1.3). Given that the association is not statistically significant, the loss mitigating benefits of nature-based infrastructure also seem to remain robust to the existence of gray infrastructure.

1.7.5 Crop Insurance Adoption

The magnitude of financial spillover effects on the federal crop insurance program may vary depending on the extent of crop insurance adoption in the county as shown in Section 1.3. For example, counties heavily reliant on crop insurance may experience a greater decrease in crop insurance claims compared to counties with low extent of insurance adoption.

I find that the flood mitigation benefits of CREP are higher in counties with a high insurance coverage level but lower in counties with a larger insured acreage (Panel E of Table 1.3). This suggests that the loss mitigating benefits of PES programs could be more significant in heavily insured counties by promoting the adoption of risk-reducing practices under extreme weather events. Conversely, the adoption of crop insurance on the extensive margin, measured by the number of insured crop acres, serves as an indicator of a county's involvement in crop production (e.g., a proxy for total planted acres), rather than the extent of loss coverage against production risk, because of substantial government subsidies on crop insurance. This distinction between the

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

number of insured acres and the coverage level potentially explains why flood mitigation benefits appear smaller in counties with a higher number of insured crop acres.

This finding indicates that the existing disparity between the federal crop insurance premium rate and the actual production risk could potentially be reduced by incorporating information from federal conservation programs into crop insurance premium calculations (Woodard et al., 2012; Woodard & Verteramo-Chiu, 2017). For instance, several Midwestern states (Iowa, Indiana, and Illinois) offer insurance premium discounts for cropland planted with cover crops (i.e., conservation cover) before the subsequent crop season. Similar premium discounts could be considered for practices that enhance streambank protection and restore wetlands.

1.7.6 Community Resilience to Natural Disaster

Lastly, the magnitude of loss mitigating benefits provided by natural infrastructure may vary depending on a county's inherent vulnerability to climate change impacts. The Community Risk Factor, a county-level measure provided by the Federal Emergency Management Agency (FEMA), aims to identify communities with higher social vulnerability and lower community resilience to natural disasters.[12] The Community Risk Factor is derived from socio-economic conditions such as race, income, age, education, housing, as well as the capacity to recover from the adverse consequences of natural hazards. The index ranges from 0.5 to 2, with higher values indicating weaker resilience to natural disasters.

I find that the magnitude of loss mitigating benefits exhibits little variation with the Community Risk Factor (Panel F of Table 1.3). This suggests that the loss mitigating benefits of

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

nature-based infrastructure established through PES programs remain robust for communities with high resilience to climate-related risks

1.8 Conclusion

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

This study contributes to existing knowledge by investigating the extent to which the introduction of CREP in the United States has reduced flooded crop losses. Since its establishment in 1998, CREP has invested billions of dollars in converting agricultural land near rivers and streams into environmentally beneficial vegetation and wetlands, with the aim of improving downstream water quality and restoring wildlife habitats. Beyond the environmental benefits, the establishment of natural infrastructure through CREP may provide co-benefits of mitigating flood risks on neighboring croplands.

To estimate the flood mitigation benefits of CREP, my identification strategy leverages variation in the timing of program introduction across counties and employs two weighted DID approaches: (i) county-specific DID using SCM and (ii) cohort-specific DID by the year of program introduction. Both empirical approaches consistently reveal that CREP significantly

mitigates flood damage on croplands. The introduction of CREP also led to a substantial reduction in insurance indemnity payouts from the federal crop insurance program, particularly in counties relying heavily on crop insurance to manage production risk in agriculture. The magnitude of these benefits varies significantly across regions and tends to increase with the duration of program availability. Overall, the flood mitigation benefits of CREP amount to 21 percent of the total program payments.

There are two caveats in interpreting the results. First, the theoretical framework suggests that PES programs that convert cropland into natural infrastructure may reduce crop loss through the conversion effect, taking at-risk cropland out of production for conservation purposes, in addition to the protection services from the established natural infrastructure to remaining cropland in production. This study finds that the conversion effect accounts for 35 percent of the estimated flood mitigation benefits of CREP, while the protection effect constitutes the remaining 65 percent. Second, the analysis excludes flood damage on uninsured cropland or relatively small crop losses not covered by the federal crop insurance program, although trends in crop insurance adoption were similar between counties with CREP and their comparison group during the study period.

Overall, this study provides robust empirical evidence that the introduction of PES programs contributes to sustainable agriculture by mitigating crop loss and provides valuable protection against increasing weather anomalies. Furthermore, the findings suggest that PES programs can enhance the sustainability of existing crop insurance programs by reducing indemnity payouts associated with weather risks. Thus, future benefit-cost analyses of PES programs should incorporate the loss mitigating benefits of established natural infrastructure, in addition to the environmental benefits, for a comprehensive evaluation of ecosystem services. These findings

underscore the critical role of PES programs in facilitating nature-based solutions for climate change adaptation.

Chapter 2: Payments and Penalties in Ecosystem Services Programs

2.1 Introduction

Payment for ecosystem services (PES) programs have been used widely in the United States and globally to incentivize agents to adopt land use or management activities that enhance environmental amenities and services. PES programs typically offer a combination of upfront and annual payments under long-term contracts (5-20 years) that specify terms of performance. In most cases, environmental benefits from these contracts require long-term vegetation growth, so it is important to ensure that agents enrolling in these programs maintain performance throughout the contract lifetime. The PES literature on agri-environmental programs to date has largely focused on incentives for initial enrollment and criteria for cost-effective targeting (see Claassen et al., 2008; Jack et al., 2008; Alix-Garcia and Wolff, 2014; Ribaudo and Shortle, 2019; Wunder et al., 2020; Baylis et al., 2022 for reviews). Little attention, however, has been paid to contract features that enhance performance *after* contracts have been signed, such as the structure of penalties for non-performance or premature contract termination.

Agents may choose to terminate signed PES contracts prior to the end of the contract lifetime for several reasons, such as an increase in foregone crop income or costs associated with the maintenance of agreed-on conservation practices for the remaining contract periods that were unexpected at the time of signing. PES contracts specify a penalty in such cases. The current standard penalty structure in US federal agricultural conservation programs such as the Conservation Reserve Program (CRP), Conservation Reserve Enhancement Program (CREP), and Environmental Quality Incentives Program (EQIP) requires participants to pay back all payments received plus interest on those payments. Direct coupling of penalties and program payments,

however, is problematic because any increase in payments simultaneously increases penalties, offsetting enhancements in participation incentives to at least some degree.

This paper examines the cost-effective structure of penalties for contract non-completion, which decouples payments and penalties. We begin with a theoretical analysis of how an agency offering PES contracts should structure its program. Because participation is voluntary, each PES contract needs to offer a combination of annual payment and non-completion penalties to maximize environmental benefits net of the total expected program costs subject to the agent's participation constraint. We then explore the principal's decision on which projects to enroll in the program to maximize environmental benefits from contracts whose terms ensure voluntary participation, subject to a constraint on overall program spending. Environmental benefits consist of those accruing from individual parcels each year while the contract remains in force, such as improvements in water quality obtained from annual reduction in pollutant loads. Our model does not extend to environmental benefits from accumulated stocks, such as sequestered carbon, which could be lost after practice removal. We compare contract structures and enrollment criteria under optimal contract terms with the standard contract terms that require participants to repay all payments received up to the date of contract termination. Finally, we conduct a numerical policy simulation to investigate the magnitudes of differences between the optimal and standard contract designs in terms of penalty schedule, rates of program participation and premature contract termination, environmental benefits, program expenditures, and penalty revenue.

Our theoretical model considers a population of heterogeneous agents who are eligible for a multi-period PES contract featuring a predetermined upfront cost-share payment for installation of a conservation practice and a series of annual payments to be made during each contract period. Opportunity costs of participation, such as foregone returns to crop production, are stochastic so

the agent's expectation of future opportunity costs is subject to change each year. If the expectation of future cropland returns less penalties for non-completion exceeds future returns from remaining in the PES contract at any point prior to the contract's termination date, the agent is expected to opt out of the contract prematurely.

The theoretical analysis yields several novel insights. We show that the optimal non-completion penalty structure is fundamentally different from the standard penalty structure. The standard penalty, which equals the sum of total payments received until contract termination, is backward-looking and rises over time. In contrast, the optimal penalty is forward-looking and equal to the principal's net future benefits lost due to premature contract termination. As a result, the optimal penalty will generally fall over time. Importantly, the optimal penalty structure decouples the penalty from the total program payments paid to the participant, increasing flexibility in contract design.

Our numerical simulation focuses on a program aimed at converting cropland to long-term conservation uses in order to reduce agricultural nonpoint source pollution. The numerical policy simulation offers two key findings. First, the optimal and standard penalty schedules are markedly different quantitatively as well as qualitatively. The standard penalty increases monotonically and more than triples over the contract lifetime. In contrast, the optimal penalty is substantially higher than the standard penalty initially, decreases monotonically and falls by over 85% on average during the contract lifetime. Second, compared to the standard contract, the optimal contract is more selective at the margin, enrolling fewer parcels while achieving a significantly higher contract completion rate among participants. Environmental benefits are greater under the optimal contract, with performance improvements increasing as the program budget gets larger. Importantly, the enhancement in program performance remains substantial even in the presence of

potential uncertainty and biases in estimating the environmental benefits of PES contracts, suggesting that the gains in performance of the optimal contract structure are due primarily to the temporal structure of penalties and are thus robust to uncertainty in estimates of environmental benefits. Overall, inefficiencies from tying penalties to total payments received can be substantial.

Our analysis has broad implications for restructuring payments and penalties for conservation programs in the US and globally. For instance, US farm legislation allocates billions of dollars in funding annually to agricultural conservation programs like CRP, CREP, and EQIP. Premature termination of PES contracts has been a consistent and growing problem in these US agricultural conservation programs. Early contract termination (non-completion) rates for conservation practices such as riparian buffers and filter strips in the CRP and CREP have tripled, rising from 2-3% of contracts signed during 1997-2000 to 7-9% during 2007-2010 (the most recent years for which all long-term contracts would have been carried through to completion). Non-completion rates for CREP contracts signed during 2011-2021 have remained in the range of 5-9%; since the terms of these latter contracts have not yet expired, final non-completion rates will likely be higher still. A study of USDA NRCS records found that 6% of EQIP contracts signed during the 1997-2000 period ended when farmers withdrew from them prematurely (Cattaneo, 2003). A subsequent analysis of NRCS records by Wallander et al. (2019) found that over 7% of EQIP contracts in fiscal year 2010 were cancelled by participants while an additional 1% were terminated by the principal for noncompliance. Cancellation rates for projects involving certain kinds of practices reached as high as 12-14%. Data from a recent study of EQIP and the Conservation Stewardship Program (CSP) in Louisiana indicate that 15% of EQIP and CSP contracts signed during 1997-2020 were cancelled while an additional 6% were terminated (Pathak et al., 2024).

The standard penalty stipulated in these Farm Bill programs is restrictive because it directly couples penalties with payments. Under the current program design, any increase in the payment level to encourage participation simultaneously creates an increase in the standard penalty that indirectly discourages participation. This inefficiency is eliminated under the optimal penalty regime that decouples the incentive payment for participation and the penalty for contract non-completion. Our numerical simulation shows that this inefficiency can be quite large.

To the best of our knowledge, this paper is the first to examine the optimal non-completion penalty structure in PES programs and derive the qualitative differences from the standard penalty commonly used in federal conservation programs in the United States. Our analysis on the optimal penalty structure is also relevant to PES programs in other countries, which commonly include the suboptimal standard penalty. Costa Rica's PES Program (PSA), Mexico's Program of Payments for Environmental Services (PSAB), Ecuador's Socio Bosque program, and the UK's Environmental Stewardship Program similarly require repayment of all funds received in cases of premature contract termination, as do PES programs in Argentina, Australia, South Korea, and the European Union (FONAFIFO, CONAFOR and Ministry of Environment 2012; Natural England 2013, Guerrero 2021).

Our analysis of the penalty structure for early termination is distinct from existing studies of PES programs, which have mainly focused on payment design and related issues for the *initial* participation decision. For instance, there is an extensive literature on payment design to increase cost-effectiveness that focuses on issues such as upfront versus annual payments (Suter et al., 2008), targeting based on performance (Babcock et al., 1997; Ferraro and Simpson, 2002; Rabotyagov et al., 2014; Howard et al., 2023), payment differentiation via auction (Ferraro, 2008; Hellerstein et al., 2015; Palm-Forster et al., 2016), and hidden information (Horowitz and Just,

2013; Mason and Plantinga, 2013). Other studies have focused on issues in the initial program participation that may not provide additional environmental services for several reasons: adverse selection (Wu and Babcock, 1996; Mezzatesta et al., 2013; Claassen et al., 2018; Lichtenberg, 2021), moral hazard incentives (Pates and Hendricks, 2020), slippage and spillovers (Wu, 2000; Roberts and Bucholtz, 2005; Lichtenberg and Smith-Ramirez, 2011; Pfaff and Robalino, 2017; Fleming et al., 2018), and interaction with other existing environmental programs (Feng et al., 2005; Feng et al., 2006; Fleming et al., 2020). Our study focuses on contract performance *ex post*.

Lastly, our study contributes to the literature on contract enforcement in the PES programs. Previous analyses have mainly focused on PES contract implementation when *ex post* monitoring to ensure compliance is costly (Choe and Fraser, 1999; Fraser, 2002, 2013; Hart and Latacz-Lohmann, 2005; Lankoski et al., 2010; Peterson et al., 2015). In contrast, our analysis focuses on *ex ante* contract provisions aimed at increasing net environmental benefits when non-compliance is observable at negligible cost.

The remainder of this study is structured as follows. Section 2.2 provides a conceptual framework of the agent's decision to participate in the multi-period PES program and the principal's optimization problem to choose the annual payment and non-completion penalty schedule *ex ante* to the agent's participation decision. Section 2.3 describes methods and data used in the numerical policy simulation based in part on existing incentives for installing riparian buffers on cropland bordering surface water bodies. Section 2.4 discusses results of the numerical policy simulation, focusing on the magnitudes of difference in penalty schedule and program outcomes of interest. Section 2.4 also discusses the robustness of the relative performance of the optimal and standard contract structures in cases where the principal relies on modeled estimates

of environmental benefits that serve as an uncertain proxy for actual environmental benefits. Section 2.5 summarizes findings and policy implications.

2.2 Theoretical Framework

This section presents a theoretical analysis of a principal's optimal selection among projects offered by agents for providing ecosystem services over multiple time periods, along with optimal design of contract terms for those projects in light of the fact that agents may find it in their interest to withdraw from contracts before the termination dates of those contracts. As discussed previously, multi-period contracts are desirable because environmental benefits derive largely from vegetation growth and thus take time to realize fully. The principal solves two sequential problems. The first is a continuous problem of choosing contract terms (payments plus penalties for premature termination) to offer to each agent for a project that achieves maximum environmental benefits net of program costs from that project. Since participation is voluntary, maximization is subject to each agent's participation constraint. The second is a discrete choice problem of selecting which projects to target for enrollment in the program given (a) the contract terms derived in the continuous problem and (b) the program's overall budget constraint.

We follow the structure of programs like the CRP, CREP, and EQIP in assuming that agents accept contracts for discrete projects (e.g., enrolling a given parcel of cropland for land retirement in the CRP or CREP). We also follow the structure of these programs in assuming that payment rates, penalties, and performance criteria are set at the time the contract is signed and remain unchanged over the contract lifetime. Fixed contract terms allow for better planning on the part of both parties. The principal typically has a fixed budget to allocate over a given time period and has limited flexibility for providing additional funds should the opportunity cost of participation rise,

putting upward pressure on payment rates, for example. Agents have the assurance of receiving payments that are fixed even if the opportunity cost of participating in the program falls (e.g., because crop prices decline).

The principal evaluates individual PES projects based on the expected program payment and environmental benefits that are independent from other PES projects (i.e., environmental benefits from each project are additively separable from environmental benefits from other projects). The assumption of additive separability of environmental benefits from conservation project is common in the literature of PES program design (Babcock et al. 1997, Wu et al. 2001, Fraser 2002, Hart and Latacz-Lohman 2005, Feng et al. 2006, Lankoski et al. 2010, Song et al. 2011). Evaluation of government-funded PES projects is similarly conducted on an individual case-by-case basis. For example, the CRP utilizes the environmental benefit index (EBI) that relies on site-specific factors for each individual land retirement project, which is separable from environmental benefits from other projects.

We begin with a two-period PES contract to derive intuition. We then generalize the analysis to a multi-period PES contract. We start with a characterization of an individual agent's decision to participate in the PES program, which incorporates the possibility of contract termination before the end of the contract lifetime due to changes in market conditions that were unexpected *ex ante*. The principal chooses the combination of program payments and penalties in the PES contract *ex ante* to maximize environmental benefits net of program costs subject to that participation constraint. Incorporating the agent's participation constraint into the principal's decision sets up a tradeoff between environmental benefits and foregone farm income. After deriving the optimal penalty and payment structure, we compare it to the current standard penalty and payment structure. We then examine how the principal with a limited budget should offer PES contracts to

a population of heterogenous agents in order to maximize environmental benefits obtainable with the funds available to it while recognizing the possibility that agents may choose to withdraw from those contracts before those contracts' expiration dates.

2.2.1 Model Setup

A principal (e.g., a government agency like the USDA or an NGO) runs a conservation program that offers long-term contracts for providing ecosystem services over a period of *t = 1, … T* years. There are $n = 1, \dots, N$ agents (e.g., farmland owners) who can provide those projects. The expected opportunity cost of providing those services in each contract year is v_{nt} $(0 \leq t \leq T - 1)$. For convenience, we will refer to these opportunity costs as foregone profit from crop production, although they could just as well consist of the costs of maintaining the conservation practices that provide ecosystem services, increased costs of pest control, or some combination of higher operating costs and lower revenue. Contract acceptance and thus the provision of ecosystem services is voluntary. The agent chooses to participate in the PES program initially if the present value of expected program returns under the contract exceeds the expected opportunity cost of participation over the contract lifetime, $\sum_{t=0}^{T-1} \delta^t v_{nt}$, where δ is a discount factor. Upon accepting the PES contract, the agent is obligated to generate ecosystem services through the conservation practices specified in the contract. Installation of the conservation practice costs k_n, a share s of which is subsidized by the principal. The contract specifies payments to the agent consisting of a series of annual payments r_n whose value is determined at the time of contract signing and remains fixed during the lifetime of the contract. If the agent terminates the contract before the expiration date, the contract specifies that the agent pays a penalty for contract non-completion at time t, p_{nt}, in addition to incurring a conversion cost to remove the conservation practice. That conversion

cost, c_{nt}, may vary over time, for example, because of vegetation growth. The contract termination decision is irreversible and observable to the principal at a negligible monitoring cost that is fixed *ex ante*. The principal and all agents are assumed to be risk neutral.

The agent maintains the measures that provide the contracted ecosystems services as long as the contract remains in force. The agent may, however, decide to withdraw from the contract if the opportunity cost increases sufficiently in any contract period. For example, a cropland owner participating in the CRP or CREP may decide to opt out of the program before the contract expiration date if a crop price shock leads the landowner to believe that the returns to reverting the land enrolled in the program to cropland (net of penalties and conversion costs) exceed the returns from keeping the land in the program. To capture this dynamic in a tractable way, we assume that each agent's expected opportunity cost over the remaining contract periods at each time t is subject to a proportional random shock ε_{nt} ($0 < \varepsilon_{nt} \leq \varepsilon_{n,max}$) and is thus $\varepsilon_{nt} \sum_{t}^{T-1} \delta^t \, v_{nt}$. For tractability, we assume that ε_{nt} is i.i.d. with density of $f_n(\varepsilon_{nt})$, mean 1, and variance σ^2, so that the initial expectation of opportunity costs over the entire contract term $E\{\varepsilon_{n0} \sum_{0}^{T-1} \delta^t \, v_{nt}\}$ is $\sum_{0}^{T-1} \delta^t \, v_{nt}$. This assumption implies that the *relative* magnitude of variability in total expected opportunity costs for the remaining contract periods is constant while the *absolute* magnitude of variability in those opportunity costs decreases during the contract lifetime.

We also assume for simplicity that, at time 0, the agent's opportunity costs of providing ecosystem services v_{nt}, the distribution of random shocks affecting those opportunity costs $f_n(\varepsilon_{nt})$, the installation costs for the conservation practice k_n, and the cost of removing the conservation practice c_{nt} are the common knowledge of the principal and agents. These common knowledge assumptions are reasonable for PES programs like CRP and CREP. Farmers have a great deal of information about their operations, especially in light of the proliferation of precision

agriculture tools and information about crop prices from USDA reports and futures market transactions. Government agencies like the USDA have at their disposal readily accessible databases containing detailed site-specific information about soils (e.g., SSURGO), cropping patterns (e.g., Cropland CROS and the Cropland Data Layer), crop productivity indices (e.g., National Commodity Crop Productivity Index), as well as time series data on crop prices, average crop yields, and average cropland rental rates, plus average crop production costs (e.g., crop budgets produced at the state and federal levels).

Each project generates a flow of environmental benefits, B_{nt}, which vary over time (e.g., as forest or grassland vegetation grows). The principal treats the time profile of those expected benefits as known *a priori* (e.g., because it relies on a model as a proxy to determine those environmental benefits or uses a predetermined formula like the EBI used to evaluate CRP projects). Conservation programs constitute a small share of the principal's investments in environmental quality, let alone its overall investment portfolio, so it is reasonable to treat the principal as risk neutral and assume that it cares only about expected benefits.

The agent's time 0 expectation of opportunity costs during each period in the contract lifetime v_{nt} and the random shocks that affect expectations of future opportunity costs in each period ε_{nt} are common knowledge, as are the costs of installing and removing conservation practices that create ecosystem services, k_n and c_{nt}, respectively. The principal offers a series of fixed annual payments r_n at each time t until the contract expires or is terminated early.[13] The principal thus chooses a combination of annual payment $r_n \geq 0$ and non-completion penalty schedule $\{p_{n1}, \ldots, p_{n,T-1}\}, (p_{nt} \geq 0 \; \forall \; t)$ to maximize the present value of program benefits net of monetary

[13] Annual payments that are fixed over the contract lifetime are attractive for both the principal and the agent. For the principal, non-varying annual payments make multi-year budget planning feasible. For the agent, fixed annual payments similarly make non-conservation investment planning easier by reducing uncertainty about future income.

outlays, which include the upfront cost-share payment for conservation practice installation, annual payments, and any penalties received. We assume that the principal only offers PES contracts to the agent if the contract has the potential to generate environmental benefits that exceed program expenditures, yielding positive net program benefits (i.e., meets a rationality condition).

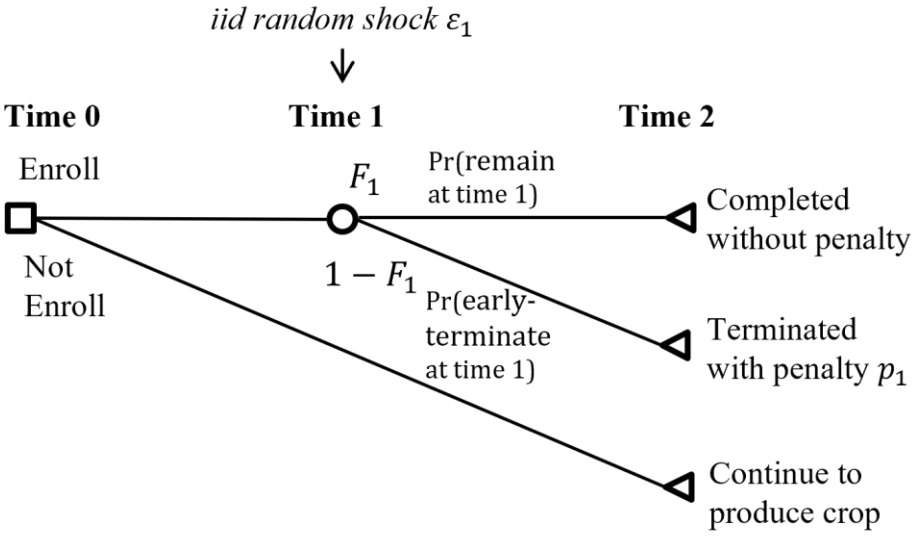
2.2.2 Two-period PES Contract

We begin with a two-period analysis of the principal's PES contract design and selection of PES projects in order to fix intuition. We later generalize the model to an arbitrary number of multiple contract periods. Figure 2.1 shows the agent's land use decisions in a PES contract that lasts two periods where the first contract period spans from time 0 to time 1 and the second contract period spans from time 1 to time 2. For instance, the agent makes decisions on program participation at time 0 and premature contract termination at time 1 (before each period starts). For ease of exposition, we treat the opportunity costs of PES program participation as consisting solely of foregone crop returns in what follows.

2.2.2.1 Probability of contract completion

When the contract covers two time periods, performance is complete if the agent decides to maintain the installed practice in time 1 (since the signed contract cannot be terminated at the time of enrollment, i.e., time 0). The agent's time 0 expected return when maintaining the contract at time 1 is equal to the second annual payment r_n. On the other hand, the agent's time 0 expected return when terminating the contract at time 1 is equal to the time 0 expected crop return for the rest of the contract period as affected by the period 1 proportional random shock, $v_{n1}\varepsilon_{n1}$, less the

Figure 2.1 Land-use path: Two-period PES contract



Note: The decision tree presents the agent's land-use path during two contract periods where the first contract period spans from time 0 to 1 and the second spans from time 1 to time 2.

time 1 penalty p_{n1} and conversion cost c_{n1}. The agent completes the project if the payment r_n exceeds the expected net return from terminating the contact. Thus, the *ex-ante* probability of contract completion is:

$$Pr(v_{n1}\varepsilon_{n1} - p_{n1} - c_{n1} \leq r_n) = Pr\left(\varepsilon_{n1} \leq \frac{r_n + p_{n1} + c_{n1}}{v_{n1}}\right) = \int_0^{\frac{r_n+p_{n1}+c_{n1}}{v_{n1}}} f_n(\varepsilon_{n1})d\varepsilon_{n1} \quad (2.1)$$
$$\equiv F_n\left(\frac{r_n + p_{n1} + c_{n1}}{v_{n1}}\right).$$

Note that the scheduled time 1 penalty directly increases the minimum level of random shock ε_{n1} that triggers contract termination at time 1, $\frac{r_n+p_{n1}+c_{n1}}{v_{n1}}$, increasing the *ex-ante* likelihood of contract completion.

2.2.2.2 Agent's Participation Constraint

At time 0, the risk-neutral agent participates in the program if the expected net program return is greater than or equal to the expected crop return for both periods, considering the early termination penalty and conversion cost at time 1. If enrolled, the agent receives the first annual payment r_n but is obligated to install the conservation practice at cost k_n with cost-share payment sk_n in the first period of the contract. In the second period, the agent's expected program return is the average return from (a) remaining in the contract at time 1, r_n, and (b) terminating the contract at time 1, $v_{n1}\varepsilon_{n1} - p_{n1} - c_{n1}$, weighted by the corresponding probabilities. Note that the penalty directly decreases the expected return from participating in the program, decreasing participation incentives indirectly as long as the ex-ante probability of contract non-completion is positive. The opportunity cost of enrolling in the program equals the time 0 expectation of crop returns over the contract lifetime. Thus, the agent's participation condition is:

$$r_n - (1-s)k_n + \delta\left[r_n F_n\left(\frac{r_n + p_{n1} + c_{n1}}{v_{n1}}\right) + \int_{\frac{r_n+p_{n1}+c_{n1}}{v_{n1}}}^{\varepsilon_{n,max}} (v_{n1}\varepsilon_{n1} - p_{n1} - c_{n1}) f_n(\varepsilon_{n1}) d\varepsilon_{n1}\right] \geq E_0\{\varepsilon_{n0}(v_{n0} + \delta v_{n1})\}. \quad (2.2)$$

2.2.2.3 The principal's Optimal Contract Structure

The principal chooses a combination of an annual payment r_n and non-completion penalty p_{n1} *ex ante* to maximize the net program benefits subject to the agent's participation condition. At time 0, the principal pays an annual rental rate r_n and a cost-share payment sk_n in return for environmental benefits obtained from the installed practice, B_{n0}. At time 1, the principal's expected net program benefits from the signed contract equal the environmental benefits from the conservation practice less the annual payment at time 1, $B_{n1} - r_n$, in case of contract completion

and the penalty, p_{n1}, in case of premature contract termination, both of which are weighted by their corresponding probabilities. Thus, the principal's contract formulation problem is:

$$\max_{r_n, p_{n1}} \; B_{n0} - r_n - sk_n + \delta\left[(B_{n1} - r_n)F_n\left(\frac{r_n + p_{n1} + c_{n1}}{v_{n1}}\right) + p_{n1}\left\{1 - F_n\left(\frac{r_n + p_{n1} + c_{n1}}{v_{n1}}\right)\right\}\right] \quad (2.3)$$

subject to the participation constraint, condition (2.2).

Since enrollment is voluntary, the principal chooses the annual payment $r_n > 0$ such that the agent's participation constraint in equation (2.2) holds with equality. Substituting the (binding) participation condition into the principal's objective function (2.3) yields the concentrated objective function:

$$\max_{r_n, p_{n1}} \; B_{n0} - k_n + \delta\left[B_{n1}F_n\left(\frac{r_n + p_{n1} + c_{n1}}{v_{n1}}\right) + \int_{\frac{r_n + p_{n1} + c_{n1}}{v_{n1}}}^{\varepsilon_{n,max}} (v_{n1}\varepsilon_{n1} - c_{n1}) f_n(\varepsilon_{n1}) d\varepsilon_{n1}\right] \quad (2.4)$$

$$-(v_{n0} + \delta v_{n1}).$$

This concentrated objective function confronts the principal with a tradeoff between environmental benefits and the opportunity cost of obtaining those benefits, e.g., foregone farm income.

The first order condition for a maximum implies an optimal penalty at time 1 equal to:

$$p_{n1}^* = B_{n1} - r_n^*, \quad (2.5)$$

Substituting the optimal penalty into the agent's participation constraint yields a closed form solution for the annual payment:

$$r_n^* = \frac{1}{1+\delta}\left[v_{n0} + \delta v_{n1} + (1-s)k_n - \delta \int_{\frac{B_{n1} + c_{n1}}{v_{n1}}}^{\varepsilon_{n,max}} (v_{n1}\varepsilon_1 - B_{n1} - c_{n1}) f_n(\varepsilon_1) d\varepsilon_1\right]. \quad (2.6)$$

Intuitively, the optimal annual payment reimburses the agent for the full opportunity cost of participation, including both expected foregone crop returns and the agent's share of the conservation practice installation cost. The agent's expected foregone crop returns are adjusted

downward for expected gains from terminating the contract prematurely, $\delta v_{n1} E\left\{\varepsilon_{n1} | \varepsilon_{n1} > \frac{B_{n1}+c_{n1}}{v_{n1}}\right\}$, net of the expected cost of converting the land back to crop production, $\delta c_{n1}\left[1 - F_n\left(\frac{B_{n1}+c_{n1}}{v_{n1}}\right)\right]$. Finally, the annual payment includes a premium consisting of the expected environmental benefits lost should the contract be terminated prematurely, $\delta B_{n1}\left[1 - F_n\left(\frac{B_{n1}+c_{n1}}{v_{n1}}\right)\right]$. This premium acts as an added incentive to keep the agent from terminating the contract before its termination date.

If the principal only wants to enroll projects in the program that generate positive net benefits, the optimal penalty is positive. The optimal penalty at time 1 is equal to the foregone environmental benefits from the conservation practice less the cost savings for the principal to maintain the contract for the remaining contract period. Intuitively, the principal requires the participant to compensate for the net program benefits lost due to early termination of the contract.

2.2.2.4 Comparison with the Standard Penalty Structure

How does the optimal penalty compare to the current standard penalty? The standard penalty structure in existing PES programs in the U.S., Mexico, Costa Rica, Ecuador, the United Kingdom, Argentina, Australia, South Korea, and the European Union is to require participants to pay back program payments received plus interest when a signed contract is terminated before its expiration date.[14]

[14] See for example the USDA's Conservation Program Manual – Part 512.57: Canceling and Terminating Contract, and Part 512.58: Recovery of Costs and Liquidated Damages ; FONAFIFO, CONAFOR and Ministry of Environment (2012); Natural England (2013); Guerrero (2021).

Let $r_n^0 > 0$ denote the minimum annual payment that binds the agent's participation constraint in equation (2.2) with equality under the standard penalty at time 1, p_{n1}^0. Then, the standard penalty at time 1 is:[15]

$$p_n^0 = \frac{1}{\delta}(sk_n + r_n^0), \tag{2.7}$$

The standard penalty is *backward* looking because it only considers payments made in the past. It thus differs qualitatively from the optimal penalty, which is *forward* looking and based on future net environmental benefits lost from premature contract termination.

The standard penalty is equal to the optimal penalty if:

$$\frac{1}{\delta}(sk_n + r_n^0) = B_{n1} - r_n^*. \tag{2.8}$$

The standard penalty is unlikely to be optimal because there is no inherent reason for total payments paid to the participant in the past (plus interest) to equal net future environmental benefits from the installed conservation practice at the time of premature contact termination.

The annual payment required to ensure an agent's enrollment in the program under the standard contract also differs from that under the optimal contract. In contrast to the optimal contract, no general closed form solution is available for the annual payment under the standard contract. Instead, the annual payment under the standard contract solves the implicit equation:

$$r_n^0 - (1-s)k_n + \delta\left[r_n^0 F_n\left(\frac{r_n^0\left(1+\frac{1}{\delta}\right)+\frac{sk_n}{\delta}+c_{n1}}{v_{n1}}\right)\right] + \tag{2.9}$$

$$\delta\int_{\frac{r_n^0\left(1+\frac{1}{\delta}\right)+\frac{sk_n}{\delta}+c_{n1}}{v_{n1}}}^{\varepsilon_{n,max}}\left(v_{n1}\varepsilon_{n1} - \frac{1}{\delta}(sk_n + r_n^0) - c_{n1}\right)f_n(\varepsilon_{n1})d\varepsilon_{n1} - v_{n0} - \delta v_{n1} = 0.$$

[15] The results from the theoretical analysis do not change qualitatively if the standard penalty is equal to only a portion of total payments paid to the participants.

2.2.2.5 Targeting Criteria under Optimal and Standard PES Contracts

Once PES contract terms are formulated, the principal chooses which projects to offer contracts to given its budget constraint at time 0. The general form of the targeting problem is the same under both the optimal and standard PES contract structures even though penalties and annual payments differ. The derivation that follows is thus valid for both. Under both the optimal and standard contracts, the principal chooses to offer a contract for a share of each agent's PES project, I_n, to maximize expected environmental benefits, taking into account the ex-ante likelihood of premature contract termination, subject to the total budget Q committed to the enrolled PES projects throughout the contract lifetime:

$$\max_{I_n} \sum_n I_n \left[B_{n0} + \delta B_{n1} F_n \left(\frac{r_n + p_{n1} + c_{n1}}{v_{n1}} \right) \right], \tag{2.10}$$

subject to:

$$\sum_n I_n \left[sk_n + r_n(1+\delta) \right] \leq Q, \tag{2.11}$$

where $0 \leq I_n \leq 1$ takes on a value of 1 if agent n is offered a contract for the full project, a value between 0 and 1 if agent *n* is offered a contract for a portion of the project, and 0 if agent *n* is not offered a contract for the project.

The budget constraint embodies an assumption that the principal allocates a fixed sum to cover all expenses committed to all contracts signed for a single cohort of agents over the entire lifetime of those contracts. In essence, we treat the principal's budget for that cohort of contracts (e.g., a single CRP signup period) as if it were deposited in an escrow account bearing interest at the rate $\frac{1-\delta}{\delta}$.

The principal's Lagrangian is:

$$\mathcal{L} = \sum_n I_n \left\{ B_{n0} + \delta B_{n1} F_n \left(\frac{r_n + p_{n1} + c_{n1}}{v_{n1}} \right) \right\} + \lambda \left\{ Q - \sum_n I_n \left[sk_n + r_n(1+\delta) \right] \right\}, \tag{2.12}$$

where λ is the shadow price of the budget constraint. Taking the derivative of the Lagrangian with respect to I_n, the optimal targeting criterion for PES projects is a benefit-cost ratio criterion:

$$\frac{B_{n0} + \delta B_{n1} F_n \left(\frac{r_n + p_{n1} + c_{n1}}{v_{n1}}\right)}{sk_n + r_n(1+\delta)} \geq \lambda. \tag{2.13}$$

As is standard, the principal offers PES contracts to agents in descending order of the ratio of expected environmental benefits to the funds expended on the project until the given budget Q is fully committed. Additionally, the principal only offers a contract to agents whose projects have positive net benefits and hence a benefit-cost ratio greater than 1 (i.e., that meets a rationality condition).

Equation (2.13) indicates that the desirability of any given PES project likely differs between the standard and optimal PES contracts because differences in (i) penalties for premature contract termination create differences in both early termination rates (and hence expected environmental benefits) and (ii) annual payments needed to induce participation. We discuss this difference in benefit-cost ratios further in the context of the more general multi-period contract.

2.2.3 Multi-period PES contract

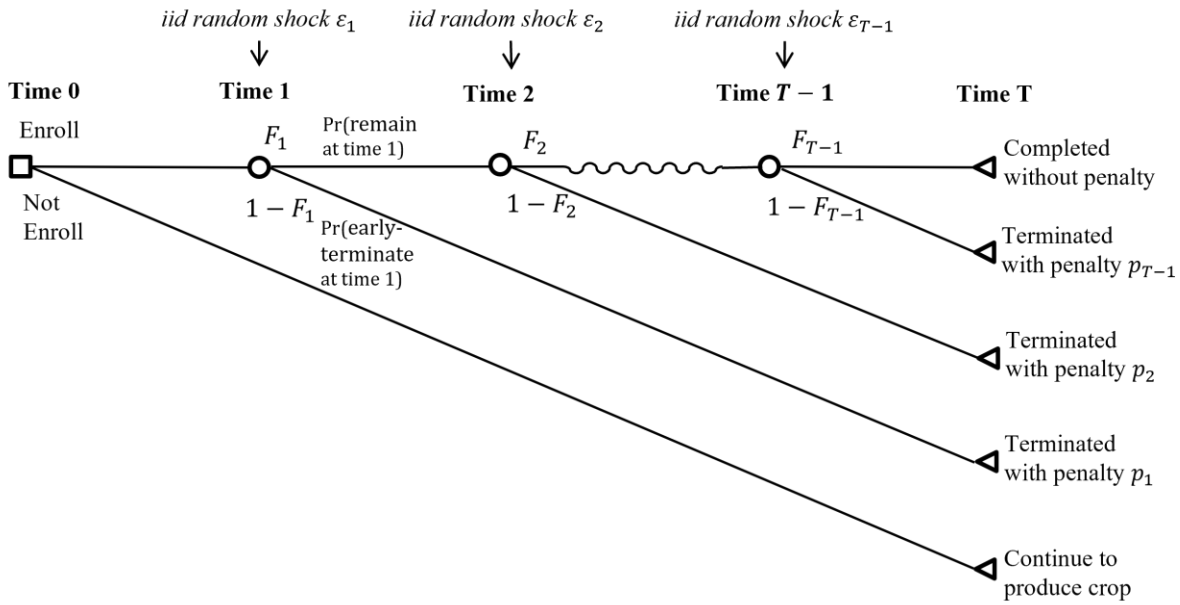
We now generalize the analysis by deriving the optimal penalty structure and annual payment in a multi-period PES contract with arbitrary contract length T. Figure 2.2 depicts the agent's multi-period decision process in this case. Appendix B presents details of the derivation.

2.2.3.1 Probability of Contract Completion

At the time of signing the PES contract (period 0), the agent anticipates opting out of the contract at any time t during the contract lifetime if the expected crop returns for the remaining contract

periods, $\varepsilon_{nt} \sum_{t}^{T-1} \delta^{t} v_{nt}$, less the penalty p_{nt} and the practice removal cost c_{nt} turn out to exceed the expected program return for the remaining contract periods, M_{nt}. For example, at time $T-1$, the agent expects to obtain an additional annual payment r_n if continuing to comply with the

Figure 2.2 Land-use path: Multi-period PES contract



Note: The decision tree presents the agent's land-use path during *T* contract periods.

contract terms, in which case $M_{nT-1} = r_n$. The expected return of maintaining the contract at time t, M_{nt}, is equal to the sum of future returns from either remaining or terminating the contract at each time t weighted by corresponding probabilities:

$$M_{nt} = r_n \tag{2.14}$$

$$+\delta \left\{ F_{nt+1} M_{nt+1} + \int_{L_{nt+1}}^{\varepsilon_{n,max}} \left[\left(\sum_{j=t+1}^{T-1} \delta^{j-t+1} v_j \right) \varepsilon_{nt+1} - p_{nt+1} - c_{nt+1} \right] f_n(\varepsilon_{nt+1}) d\varepsilon_{nt+1} \right\}$$

where the minimum level of random shock that triggers contract termination at time t, L_{nt}, is:

$$L_{nt} \equiv \frac{M_{nt} + p_{nt} + c_{nt}}{\left(\sum_{j=t}^{T-1} \delta^{j-t} v_{nj} \right)}, \qquad 1 \le t \le T-1. \tag{2.15}$$

The agent remains in compliance with the signed contract at time t when the proportional random shock at time t, ε_{nt}, is too small to make contract non-completion desirable for the agent. The agent's *ex-ante* probability of maintaining the contract at time t, F_{nt}, can be expressed as:

$$F_{nt} \equiv Pr(\varepsilon_{nt} \leq L_{nt}) = \int_0^{L_{nt}} f_n(\varepsilon_{nt}) d\varepsilon_{nt}, \qquad 1 \leq t \leq T-1. \tag{2.16}$$

Note that $F_{n0} = 1$ because the signed contract cannot be terminated at the time of enrollment.

Lastly, the *ex-ante* survival probability of the contract at time t is a joint product from F_{n1} to F_{nt}:

$$\prod_{j=1}^{t} F_{nj}, \tag{2.17}$$

where the *ex-ante* likelihood of contract completion is obtained when $t = T-1$ in equation (2.17). Note that the scheduled penalty from time 1 to $T-1$ directly increases the agent's incentive to complete the contract by increasing L_{nt} in equation (2.15) and thus increasing F_{nt} in equations (2.16) and (2.17).

2.2.3.2 Agent's PES Program Participation and Contract Completion Decisions

At time 0, the risk-neutral agent enrolls in the PES program if the present value of expected returns from enrollment exceeds the expected opportunity costs of participation over the T contract periods. As in the two-period contract, if enrolled, the agent receives the annual payment r_n less the out-of-pocket costs of installing the conservation practice $(1-s)k_n$. From time 1 to $T-1$, the agent's expected return during the contract period is the sum of returns when the contract is either maintained or terminated at each time 1 to $T-1$ weighted by corresponding probabilities

in each period. The agent's opportunity cost of providing ecosystem services instead of producing a crop is equal to the present value of crop returns during T contract periods.

The agent's participation condition is:

$$(1-s)k_n + \left(\prod_{t=1}^{T-1} F_{nt}\right)\left(\sum_{t=0}^{T-1} \delta^t r_n\right) \tag{2.18}$$

$$+\sum_{j=0}^{T-2}\left\{\left(\prod_{t=0}^{j} F_{nt}\right)\int_{L_{nj+1}}^{\varepsilon_{n,max}}\left[\sum_{l=0}^{j}\delta^l r_n + \left(\sum_{q=j+1}^{T-1}\delta^q v_{nq}\right)\varepsilon_{nj+1}\right.\right.$$

$$\left.\left. - \delta^{j+1}\left(p_{nj+1}+c_{nj+1}\right)\right] f_n\left(\varepsilon_{nj+1}\right)d\varepsilon_{nj+1}\right\}$$

$$\geq E_0\left\{\varepsilon_{n0}\sum_{t=0}^{T-1}\delta^t v_{nt}\right\} = \sum_{t=0}^{T-1}\delta^t v_{nt}.$$

The left-hand side of condition (2.18) represents the time 0 expected net program return to the agent: (i) the out-of-pocket cost to install the riparian buffer plus (ii) a series of annual payments weighted by the probability of contract completion plus (iii) the sum of expected returns when the agent opts out of the contract at each time 1 to $T-1$ weighted by the corresponding probabilities of contract non-completion. Note that the expected return in case of contract non-completion consists of annual program payment received up to the time *j* (the last year before the premature contract termination at time $j+1$) and annual crop return from time $j+1$ to $T-1$, netting out the penalty and practice removal cost. The right-hand side of this condition represents the time 0 expected net crop return for T periods, that is, the agent's expected opportunity cost of program participation.

2.2.3.3 The Principal's Optimal Contract Terms

In the multi-period PES contract, the principal chooses a combination of annual payment r_n and non-completion penalty structure p_{nt} $(1 \leq t \leq T-1)$ *ex ante* to offer the agent in order to maximize net program benefits subject to the agent's participation condition. At time 0, the principal pays the cost-share payment sk_n and annual rental payment r_n in return for environmental benefits obtained from the installed practice, B_{n0}. From time 1 to $T-1$, the principal's expected net program benefits from the signed contract are equal to the average of environmental benefits from the conservation practice less the annual payment, $B_{nt} - r_n$, in the case of maintaining the contract at time t and the penalty, p_{nt}, in the case of contract termination at time t, each weighted by corresponding probabilities. Thus, the principal's contract formulation problem is:

$$max_{r_n, p_1, p_2, \ldots, p_{T-1}} - sk_n + \left(\prod_{t=1}^{T-1} F_{nt}\right)\left(\sum_{t=0}^{T-1} \delta^t (B_{nt} - r_n)\right) \tag{2.19}$$

$$+ \sum_{j=0}^{T-2} \left(\prod_{t=0}^{j} F_{nt}\right)(1 - F_{nj+1}) \left[\sum_{l=0}^{j} \delta^l (B_{nl} - r_n) + \delta^{j+1} p_{nj+1}\right],$$

subject to the participation constraint, condition (2.18).

The principal chooses the minimum annual payment r_n such that the agent's participation constraint in condition (2.18) holds with equality. Substituting the binding participation condition into the principal's objective function (2.19) yields the concentrated objective function:

$$max_{r_n, p_1, p_2, \ldots, p_{T-1}} - k_n + \left(\prod_{t=1}^{T-1} F_{nt}\right)\left(\sum_{t=0}^{T-1} \delta^t B_{nt}\right) \tag{2.20}$$

$$+ \sum_{j=0}^{T-2} \left\{ \left(\prod_{t=0}^{j} F_{nt}\right) \int_{L_{nj+1}}^{\varepsilon_{n,max}} \left[\sum_{l=0}^{j} \delta^l B_{nl} + \left(\sum_{q=j+1}^{T-1} \delta^q v_{nq}\right) \varepsilon_{nj+1} - \delta^{j+1} c_{nj+1}\right] f_n(\varepsilon_{nj+1}) d\varepsilon_{nj+1} \right\}$$

$$-\sum_{t=0}^{T-1} \delta^t \, v_{nt}.$$

As in the two-period case, the concentrated objective function incorporates a tradeoff between environmental benefits and society's opportunity cost in terms of foregone farm income.

For a given T-period PES contract, the optimal penalty schedule from time 1 to time $T-1$ satisfies a set of T first order conditions, one for each contract period $t = 0, \ldots T-1$. As we show in Appendix B, the optimal penalty p_{nt}^* for any T-period PES contract is:

$$p_{nt}^* = \frac{1}{\delta^t}\left[\sum_{j=t}^{T-1} \delta^j \left(B_{nj} - r_n^*\right)\right], \quad 1 \le t \le T-1. \tag{2.21}$$

As in the two-period case, the annual payment under the optimal contract r_n^* is chosen to make the agent's participation constraint in condition (2.18) bind with equality. Substituting the optimal penalty p_{nt}^* into the participation constraint yields a closed form expression for the annual payment analogous to the two-period solution:

$$r_n^* = \tag{2.22}$$

$$\frac{1}{\sum_{t=0}^{T-1}\delta^t}\Bigg(\sum_{t=0}^{T-1}\delta^t \, v_{nt} + (1-s)k_n - \sum_{j=0}^{T-2}\Bigg\{\left(\prod_{t=0}^{j} F_{nt}^*\right)\int_{L_{nj+1}^*}^{\varepsilon_{n,max}}\Big[\left(\sum_{q=j+1}^{T-1}\delta^q \, v_{nq}\right)\varepsilon_{nj+1} -$$

$$\delta^{j+1}c_{nj+1}\Big]f_n\left(\varepsilon_{nj+1}\right)d\varepsilon_{nj+1}\Bigg\} + \sum_{j=0}^{T-2}\left\{\left(\prod_{t=0}^{j} F_{nt}^*\right)\left(1 - F_{nj+1}^*\right)\sum_{q=j+1}^{T-1}\delta^q \, B_{nq}\right\}\Bigg)$$

As in the two-period case, the first term on the right hand side of equation (2.22) is the agent's expected opportunity cost of participation, including foregone crop returns and the agent's share of the conservation practice installation cost. The second term adjusts the agent's expected opportunity cost of participation downward for expected gains from terminating the contract prematurely net of the costs of converting the land back to production status. The third term is a supplement designed to offset expected penalties.

The optimal penalty in equation (2.21) at time t is equal to the time t value of remaining environmental benefits less the annual payments from time t to the date of contract expiration. Thus, we have:

Proposition 1. *The optimal non-completion penalty structure in the PES contract compensates the principal for the future net benefits lost due to premature contract termination.*

Proposition 1 provides several insights into PES contract design. First, under the optimal penalty structure, the principal secures the monetary value of expected net program benefits from each signed contract because the penalty compensates for net environmental benefits lost due to contract non-completion. Second, the optimal penalty will generally vary across parcels. For instance, parcels with similar soil productivity and thus receiving the same annual payment may have different runoff potential due to differences in crops being grown, permeability of soils, topography, and similar factors. In such cases, contracts for parcels with greater potential for runoff reduction will feature higher penalties for contract non-completion. We discuss these issues at greater length in the next section.

It follows from equation (2.21) defining the optimal penalty structure that the year-to-year change in the optimal penalty level at each time t is:

$$\delta p_{nt+1}^{*} - p_{nt}^{*} = -(B_{nt} - r_{n}^{*}). \tag{2.23}$$

Since the principal is assumed to enroll only parcels that generate environmental benefits that exceed payments over the contract lifetime, $\sum_{0}^{T-1}\{B_{nt} - r_{n}^{*}\} > 0$ it follows that $B_{nt} - r_{n}^{*} > 0$ for some, if not all t. Exceptions likely occur only in the very early years of the contract, for example, during the time before vegetation in the installed conservation practice has grown enough to provide substantial annual environmental benefits. We thus have:

Proposition 2. *The optimal non-completion penalty generally decreases over time.*

Since total environmental benefits to be obtained for the remaining contract periods generally decline as the contract approaches its expiration date, the optimal penalty declines over time as well. If the annual environmental benefits are less than the annual payment, however, the optimal penalty increases over time to make up the loss incurred by the principal. It is thus possible that the penalty schedule will have an inverted U shape, with penalties increasing over time in very early contract periods when current environmental benefits are low but future benefits are high. Intuitively, the optimal penalty credits net environmental benefits received in each period by reducing the non-completion penalty over time.

2.2.3.4 Comparison with Standard Contract Terms

The standard penalty schedule is:

$$p_{nt}^{0} = \frac{1}{\delta^{t}}\left[sk_n + \left(\sum_{j=0}^{t-1} \delta^{j}\, r_n^{0}\right)\right], \tag{2.24}$$

where r_n^0 is set such that the agent's participation constraint holds with equality under the standard penalty, as in the two-period case:

$$(1-s)k_n + \left(\prod_{t=1}^{T-1} F_{nt}^{0}\right)\left(\sum_{t=0}^{T-1} \delta^{t}\, r_n^{0}\right) \tag{2.25}$$

$$+\sum_{j=0}^{T-2}\left\{\left(\prod_{t=0}^{j} F_{nt}^{0}\right)\int_{L_{nj+1}^{0}}^{\varepsilon_{n,max}}\left[\sum_{l=0}^{j}\delta^{l}\, r_n^{0} + \left(\sum_{q=j+1}^{T-1}\delta^{q}\, v_{nq}\right)\varepsilon_{nj+1}\right.\right.$$

$$\left.\left. - \delta^{j+1}\left(p_{nj+1}^{0} + c_{nj+1}\right)\right] f_n\left(\varepsilon_{nj+1}\right) d\varepsilon_{nj+1}\right\} - \sum_{t=0}^{T-1}\delta^{t}\, v_{nt} = 0.$$

Note that L_{nt}^{0} and F_{nt}^{0} denote the minimum level of random shock that triggers contract termination at time t and the *ex-ante* probability of maintaining the contract at time t under the standard contract, respectively (i.e., equations (2.15) and (2.16) under the standard contract).

The standard penalty schedule differs qualitatively from the optimal penalty schedule in the same manner as in the two-period case: The standard penalty is backward-looking because it is equal to the total payments made in the past contract periods while the optimal penalty schedule is forward-looking and is equal to net environmental benefits lost for the remaining contract lifetime due to premature termination. In essence, the current standard penalty structure commits the agent to offering a money-back guarantee: A agent who terminates the PES contract before its expiration date (or otherwise fails to comply with the terms of the contract) is obligated to refund all monies received. In contrast, the optimal penalty ensures that the principal gets the environmental benefits it contracted for in either physical or monetary terms.

Both the optimal and standard contracts feature penalty structures that vary across individual participants. The way in which they vary across participants differs, however. The standard penalty varies across participants because of differences in the opportunity cost of participating, which determines payment rates (the rental rate in the case of CRP, or the soil rental rate in the case of CREP). The optimal penalty varies across participants because of variations in net environmental benefits, that is, because of the relationship between environmental benefits and the opportunity cost of participation.

It is immediately apparent from comparison of equations (2.21) and (2.24) that the optimal penalty is decreasing in the annual payment rate while the standard penalty is increasing in it. Thus, under the standard penalty, attempts to increase participation by raising the annual payment rate are directly attenuated by increases in potential penalties of comparable magnitude; discounting is

the only reason why this offset is not one-for-one. In contrast, under the optimal penalty schedule any increase in the annual payment rate actually decreases penalties levied for non-completion, as the optimal penalty design effectively decouples participation and performance incentives.

The standard penalty schedule is equal to the optimal penalty schedule if:

$$\frac{1}{\delta^t}\left[sk_n + \left(\sum_{j=0}^{t-1} \delta^j \, r_n^0\right)\right] = \frac{1}{\delta^t}\left[\sum_{j=t}^{T-1} \delta^j \left(B_{nj} - r_n^*\right)\right], \quad 1 \le t \le T-1. \tag{2.26}$$

This equality will hold only under exceptional circumstances, as there is no inherent reason for past payments to equal future net environmental benefits. Moreover, in contrast to the optimal penalty, the standard penalty increases monotonically over time:

$$\delta p_{nt+1}^0 - p_{nt}^0 = r_n^0 > 0. \tag{2.27}$$

Since the optimal penalty is either monotonically decreasing or inverse U-shaped over time, the time paths of the two penalty structures cross at most twice. Thus,

Proposition 3. *The standard penalty equals the optimal penalty in at most two periods during the contract lifetime.*

The optimal penalty is likely to be less than the standard penalty when the annual program payment is relatively large compared to the annual environmental benefits obtained from the conservation practice adoption. In this case, net benefits lost due to contract non-completion are not large and, thus, gains from increasing the likelihood of contract completion with large penalty may not outweigh simultaneous losses in the agent's participation incentive. The optimal penalty is also likely to be lower than the standard penalty as the contract approaches the expiration date. The standard penalty always peaks in the last contract period when the total payments are the greatest and future net benefits are the lowest.

The optimal penalty is likely to be greater than the standard penalty when the contract generates relatively high environmental benefits at low cost for the remaining contract periods. In this case, preventing contract early termination with a large penalty generally leads to greater net environmental benefits that outweigh any loss in participation incentives. In contrast, the standard penalty fails to make up for any loss in net environmental benefits that is greater than the total financial incentives paid to the participant. The optimal penalty is also likely to be greater than the standard penalty in the early contract periods when the total program payments are low and the expected net program benefits for the remaining contract periods are large.

2.2.3.5 Optimal Targeting Criteria

As in the two-period case, the principal chooses to offer a contract for a share of each agent's PES project, I_n, to maximize the expected environmental benefits, taking into account the ex-ante likelihood of premature contract termination in each period t, subject to the budget Q committed throughout the contract lifetime T:

$$\max_{I_n} \sum\nolimits_n I_n \left[\left(\prod_{t=1}^{T-1} F_{nt} \right) \left(\sum_{t=0}^{T-1} \delta^t B_{nt} \right) + \sum_{j=0}^{T-2} \left(\prod_{t=0}^{j} F_{nt} \right) \sum_{l=0}^{j} \delta^l B_{nl} \right], \tag{2.28}$$

subject to:

$$\sum\nolimits_n I_n \left[sk_n + \sum_{t=0}^{T-1} \delta^t r_n \right] \leq Q. \tag{2.29}$$

The Lagrangian is:

$$\mathcal{L} = \sum\nolimits_n I_n \left\{ B_{n0} + \delta B_{n1} F_n \left(\frac{r_n + p_{n1} + c_{n1}}{v_{n1}} \right) \right\} + \lambda \left\{ Q - \sum\nolimits_n I_n \left[sk_n + r_n (1+\delta) \right] \right\}, \tag{2.30}$$

where λ is the shadow price of the budget constraint. Taking the derivative of the Lagrangian with respect to I_n, the optimal targeting criterion for PES projects is a benefit-cost ratio criterion:

$$\frac{1}{sk_n + \sum_{t=0}^{T-1} \delta^t r_n} \left[\left(\prod_{t=1}^{T-1} F_{nt} \right) \left(\sum_{t=0}^{T-1} \delta^t B_{nt} \right) + \sum_{j=0}^{T-2} \left(\prod_{t=0}^{j} F_{nt} \right) \sum_{l=0}^{j} \delta^l B_{nl} \right] \geq \lambda \qquad (2.31)$$

As in the two-period case, equation (2.31) provides two insights. First, the principal would offer the optimized PES contract to agents in descending order of the project's benefit-cost ratio until the budget is fully committed. Second, the desirability of PES projects will generally differ between the standard and optimal PES contracts due to differences in both penalty structure and annual payments, which also alter the ex-ante likelihood of contract completion.

To compare the desirability of an individual project under the standard and optimal PES contracts, we divide the benefit-cost ratio under the optimal contract by the benefit-cost ratio under the standard contract. The resulting ratio can be written:

$$\left[\frac{sk_n + \sum_{t=0}^{T-1} \delta^t r_n^0}{sk_n + \sum_{t=0}^{T-1} \delta^t r_n^*} \right] \times \left[\frac{(\prod_{t=1}^{T-1} F_{nt}^*)(\sum_{t=0}^{T-1} \delta^t B_{nt}) + \sum_{j=0}^{T-2} \left(\prod_{t=0}^{j} F_{nt}^* \right) \sum_{l=0}^{j} \delta^l B_{nl}}{(\prod_{t=1}^{T-1} F_{nt}^0)(\sum_{t=0}^{T-1} \delta^t B_{nt}) + \sum_{j=0}^{T-2} \left(\prod_{t=0}^{j} F_{nt}^0 \right) \sum_{l=0}^{j} \delta^l B_{nl}} \right] \qquad (2.32)$$

Intuitively, the change in desirability of any individual project due to switching from standard contract terms to optimal ones depends on how that switch affects the likelihood of premature termination versus annual payments. If the likelihood of premature termination is lower under the optimal contract than the standard contract, expected environmental benefits over the lifetime of the project are greater and thus the second term in square brackets is greater than one. If annual payments are lower under the optimal contract than the standard contract, the first term in square brackets is also greater than one, so that any individual project has a higher benefit-cost ratio under optimal contract terms than under standard contract terms. However, a lower likelihood of premature contract termination suggests that annual payments are likely to be higher under optimal contract terms than under standard contract terms, in which case the first term in square brackets is less than one. In that case, whether switching from a standard contract to an optimal contract

makes a project more desirable depends on the magnitude of the increase in expected environmental benefits relative to the increase in annual payments.

2.3 Numerical Policy Simulation Methods

We conduct a numerical policy simulation with three main objectives. First, we investigate the quantitative and qualitative differences of the non-completion penalty schedules over time under optimal and standard contract structures. Second, we explore the magnitudes of differences in the PES program outcomes between these two contract structures, such as program participation rate and premature termination rate of the signed contracts, environmental benefits obtained subject to a constraint on spending commitments, program expenditures, and penalty revenue. Third, we examine how the magnitude of difference in program outcomes under the two contracts varies with program size (as measured by budget).

The numerical simulation is based in part on the main features of CREP contracts for riparian buffer installation. CREP is the primary federal program that incentivizes installation of riparian buffers in the United States (Hellerstein, 2017). Landowners who enroll in CREP agree to convert cropland in the riparian zone into a grass or forest while continuing to operate cropland outside the riparian zone. In return, CREP offers a cost-share payment for riparian buffer installation expenses and a series of annual rental payments. Contract periods range from 10 to 15 years, depending on the type of buffer installed. The landowner may terminate the contract before the expiration date but faces a financial penalty if she does so.

We operationalize the numerical simulation using data from the Chesapeake Bay watershed. CREP is of significant policy interest in this context because it plays a central role in plans for meeting the EPA mandated total maximum daily load (TMDL) requirements for agricultural

nutrient and sediment runoff into the Chesapeake Bay. The Bay TMDL regulation is the largest ever developed by the EPA. As explained below, the simulation model parameters are based on data from the EPA-funded Chesapeake Bay Watershed Model (CBWM), studies of nutrient removal by riparian buffers, and USDA estimates of cropland soil rental rates and relative crop productivity.

Our simulation model incorporates spatially heterogeneous environmental benefits and crop profitability across agricultural parcels in the Chesapeake Bay region. We use the spatially explicit parcel-level tax assessor database obtained from Maryland Department of Planning to determine the location and size of individual agricultural parcels for all counties in Maryland. Specifically, we identify agricultural parcels in Maryland that are potentially eligible for PES contracts aimed at converting cropland into grass riparian grass buffer for a 10-year contract period. We use two criteria to determine eligibility: parcels must have (a) at least 10 acres of cropland on the entire landowner parcel and (b) at least 0.1 acres of cropland in the 100-foot riparian buffer zone bordering the waterbody. First, we use high-resolution (1-meter) land use/land cover data from the EPA's Chesapeake Bay Program to identify the presence and size of cropland within each parcel.[16] This dataset is derived from aerial imagery captured in 2017-2018 and distinguishes cropland from other land types (e.g., forest, wetlands, water, hay/pasture, urban impervious, etc.). Second, we overlay the parcel boundaries with the United States Geological Survey (USGS) National Hydrography Data to select agricultural parcels containing or located adjacent to streams, rivers, or wetlands, which also have minimum of 0.1 cropland acres within 100-foot riparian buffer zone on the parcel. After applying these two criteria, we identified a total of 7,223 parcels that are

[16] The Chesapeake Bay Program's land use/land cover data and descriptions are available at: https://www.chesapeakeconservancy.org/conservation-innovation-center/high-resolution-data/lulc-data-project-2022/

potentially eligible for the PES program. These parcels have an average of 4.7 cropland acres and standard deviation of 9.2 cropland acres within the 100-foot buffer zone eligible for grass buffer installation.

2.3.1 Landowner's Opportunity Cost of Land

The landowner's opportunity cost of program enrollment equals the expected returns to crop production during future contract periods, which is modified by a multiplicative random shock in each contract period. We first provide a brief description of the approach to calculate expected annual crop returns that vary across parcels (see Appendix B for further details on the calculation methods). Then, we describe the method to obtain the distribution of the random shock, which is assumed to be common for all parcels.

To obtain parcel-level annual crop returns, we begin with statewide expected annual returns from producing corn, which is the primary crop grown in Maryland, reported by the University of Maryland's 2021 crop budget. The statewide average net return to corn production is calculated as the weighted average of gross revenue less variable and annualized fixed costs for no-till corn and conventional-till corn on non-irrigated cropland, estimated at $249.4 per acre in 2020 dollar terms using the Consumer Price Index (CPI). The share of corn acreage by tillage practices is obtained from the USDA's National Agricultural Statistics Service (NASS) 2022 Maryland Tillage Estimates.

To account for spatial heterogeneity in crop profitability across parcels, two adjustments are made to the statewide average crop return. First, we measure county-specific crop profitability relative to the statewide average by calculating the ratio of county-level soil rental rates for non-irrigated cropland in 2020 obtained from the USDA's NASS to the statewide average. Second,

parcel-specific soil productivity, relative to other parcels within the same county, is assessed using the National Commodity Crop Productivity Index (NCCPI) obtained from the USDA's Natural Resources Conservation Service. We calculate the area-weighted NCCPI for corn in a 100-foot riparian buffer zone and obtain the parcel's proportional deviation from the county average. These two relative measures of crop profitability are then multiplied by the statewide annual crop return to yield parcel-level crop returns. On average, the landowner's time 0 expectation on annual crop return is estimated to be $281.30/acre, with a standard deviation of $116.10/acre.

The landowner's time 0 expectation of crop return during future contract periods is subject to change by a proportional random shock with mean 1. We assume that expectations about future crop returns are based on observed past crop returns and formed by an autoregressive process. Random shocks equal deviations from that autoregressive process. Due to the limited availability of crop return time series data, we use statewide gross revenue as a proxy for net crop returns. Since we are interested in proportional shocks, we use a logged autoregressive process to estimate those deviations:

$$ln\left(\frac{y_t}{y_{t-1}}\right) = \gamma + \beta_1 ln(y_{t-1}) + \beta_2 ln(y_{t-2}) + \cdots + \beta_h ln(y_{t-h}) + u_t, \qquad (2.33)$$

where y_t is the statewide crop return at time t and β_1, β_2, ..., β_h represent contribution of crop returns in the most recent lagged h years. The expression $exp(\hat{u}_t)$ equals the proportional deviation of y_t relative to expectation, which is common to all landowners.[17]

[17] There is little consensus about how the expectation on crop return in the current year interacts with that in the past and the future years. Prior studies find mixed evidence about the stationarity of crop return (Schatzki, 2003; Song et al., 2011). Studies of producer's supply response to crop price presents little consensus on a single best proxy for farmer's price expectation because it is subject to vary across commodity, geography, and institutional setting (Askari and Cummings, 1977; McIntosh and Shumway, 1994; Sanderson et al., 1980). Factors used in the literature to formulate farmer's crop price expectation include the future, current, and past crop prices as well as the principal support price (Gardner, 1976; Parrott and McIntosh, 1996).

We use USDA NASS data on annual per-acre corn yield and price received in Maryland for the past 70 years, a period that corresponds to the era of contemporary agriculture (1951-2020). Annual gross revenue is a product of the annual per-acre yield and price received. A correlogram indicates that revenue lags of more than four years have no discernible correlation with current revenues, so we estimate equation (2.33) for lags of one to four years. The AR(4) process fit the data best. We then used the values of $exp(\hat{u}_t)$ calculated from errors of the AR(4) model to parameterize a lognormal distribution of random shock in Figure 2.3. The lognormal distribution has mean 1.03 and standard deviation 0.26.[18]

2.3.2 Riparian Buffer Installation and Removal Costs

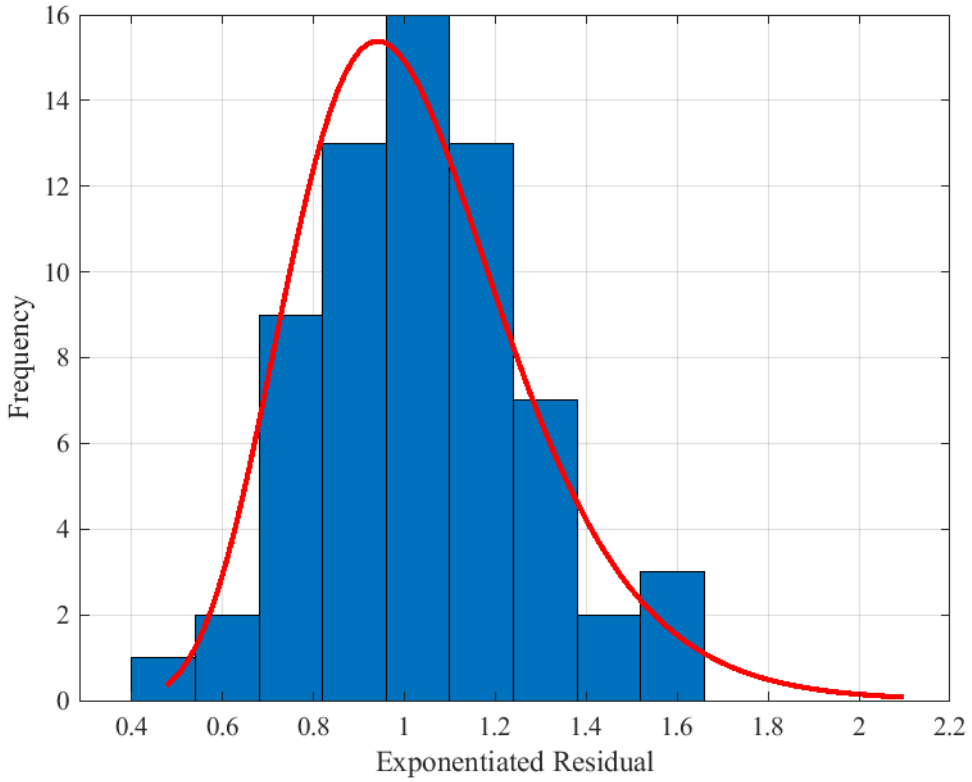
Enrolling in the PES program obligates a landowner to install a riparian buffer on cropland. We use the installation cost of a grass buffer, which averages $317.8 per acre in 2020 dollar terms, with a range from $40.3 to $527.9 per acre (Price et al., 2019). PES programs typically provide cost-share funding for installation costs at rates ranging from 50 percent to 100 percent. We set the cost-share at 50 percent (s = 0.5) as a baseline.

In the case of contract non-completion, the enrolled landowner needs to convert the installed buffer back to cropland and thus incurs a removal cost, in addition to any penalty. Converting grass cover to cropland involves both chemical treatment with herbicides and mechanical operations such as mowing, and tillage. The buffer removal cost is likely to be lower than the installation cost and expected to vary across regions (Miao et al., 2014). We set the baseline value of the buffer

[18] Distributions of the random shock ε_{nt} derived from the AR(1), AR(2), and AR(3) models were very similar to that derived from the AR(4) model.

removal cost to half of the buffer installation cost, $158.9/acre, and assume it remains fixed during the contract lifetime, as is reasonable for grass buffers.[19]

Figure 2.3 Distribution of the random shock



Note: The histogram represents the principal's and agent's common assessment of proportional random variations in initial expectations of crop returns during the remaining contract period. Each observation is a proportional deviation of corn gross revenue from expectation that is unexplained by recent four lagged years of gross revenues, that is, the exponentiated residual from equation (2.33). A total of 70 observations of annual corn gross revenue in Maryland from USDA-NASS are used (1951-2021) to estimate the equation (2.33). A log-normal distribution is fitted to the histogram to obtain the distribution of the random shock.

[19] Miao et al. (2014) use $15/acre for the cost of converting well-managed pasture to cropland in their simulation of land use change in North Dakota. Ransom et al. (2008) estimate $54.62/acre for the cost of converting CRP grass to cropland using farm survey in North Dakota. The cost consists of chemical cost and machinery cost. Lyon and Holman (2009) estimate the cost of converting CRP grass into cropland for wheat and millet to be $88.9/acre (reduced-till), $170.93 (conventional till), and $177.77/acre (no-till) in Nebraska. Jones and Fischbacher (2018) estimate the cost of converting CRP grass to cropland to be $100-125/acre for wheat and $150-175/acre for sorghum in Texas.

2.3.3 Environmental Benefits of Riparian Buffer Adoption

Riparian buffers are known to be highly effective in reducing agricultural nonpoint source pollutants as well as providing several ecosystem services such as wildlife habitat, aquatic ecosystem enhancement, carbon sequestration, and reductions in stream bank erosion (Lee et al., 2003; Belt et al., 2014; Sweeney and Newbold, 2014). For simplicity, we focus on downstream water quality benefits of converting cropland to riparian grass buffer using parameters from the CBWM. The CBWM is used by the EPA and the Bay states to credit the impact of conservation practices on the nutrient and sediment reductions to meet the Chesapeake Bay TMDL requirements. CBWM parameters have also been used by other recent papers to estimate the environmental benefits of conservation programs and evaluate the cost-effectiveness of different policy designs (Fleming et al., 2018; Fleming et al., 2020).[20]

The total water quality benefits of installing the riparian buffer on cropland consist of direct and indirect benefits. The direct benefit is the reduction of pollutant loads when the cropland within the riparian zone is replaced with the grass buffer. Cropland is a high loading source due to the higher application of fertilizer and greater soil erosion compared to grass cover. The indirect benefit is the reduction of pollutant loads when the grass buffer filters nutrient runoff and sediment delivered from adjacent cropland before they can reach surface water. Figure B2 in Appendix B presents the estimated time profile of total water quality benefits of converting cropland to grass riparian buffer for the 10 years after buffer installation based on the reduction of total nitrogen, phosphorus, and sediments delivered from cropland to the Chesapeake Bay (see Appendix B for the detailed calculations of the environmental benefits).

[20] Details on the Chesapeake Bay Watershed Model and Chesapeake Assessment Scenario Tool are available at: http://www.chesapeakebay.net/data and https://cast.chesapeakebay.net.

The direct benefit of reducing pollutant loads from converting cropland to grass buffer is immediate and stays at the same level over the contract lifetime. The direct benefit varies spatially based on the specific county and land-river segment where the parcel is located. Land-river segments are watersheds designated in the CBWM that are generally more localized in scope compared to the USGS's 8-digit Hydrologic Unit Code because they are designed to analyze the flow of water, sediment, pollutants, and other factors within the watershed. Converting an acre of cropland to grass cover reduces annual nitrogen, phosphorus, and sediment runoff from the farm field to the Chesapeake Bay by 15.4 pounds, 0.17 pounds, and 422.5 pounds on average, across the 7,223 program-eligible parcels. We convert this pollutant load reduction into monetary value using per-pound social cost of each nutrient load in the Bay: $14.96/pound for nitrogen, $181.61/pound for phosphorus, and $0.37/pound for sediment in year 2015 dollars (Choi et al., 2020). Converting these costs to 2020 levels using the CPI gives estimated total direct water quality benefits of converting cropland to grassland equal to $457.1/acre per year on average.

The indirect benefit of buffers consists of reductions in nutrient and sediment runoff from adjacent cropland draining into the buffer area. This indirect benefit increases over time as the grass matures and varies spatially across hydrogeomorphic regions, counties, and land-river segments (Hairston-Strang, 2005; Simpson and Weammert, 2009; Belt et al., 2014). We construct the time profile of nutrient and sediment removal rate for the grass buffer based on parameters from the CBWM and assumptions supported by the literature (see Appendix B for additional details). On average, the established riparian grass buffer reduces annual nitrogen, phosphorus, and sediment runoff from neighboring crop field to the Chesapeake Bay by 15.6%, 20.7%, and 27.6% in the first year of establishment and 31.1%, 41.4%, and 55.2% in the end of contract

lifetime. Indirect benefits of the grass buffer increase from $329.4/acre to $658.2/acre, on average, over the 10 years after the buffer installation.

2.3.4 Contract Terms Offered

We simulate policy outcomes of interest under the optimal and standard PES contracts that differ in terms of annual payment and penalty schedule. The optimal contract offered to agents is obtained as follows. First, the annual payment in equation (2.22) is obtained using the time profile of environmental benefits, riparian buffer installation and removal costs, expected foregone crop returns, and the distribution of random shock. The optimal penalty schedule p_{nt}^{*} in equation (2.21) is obtained using the time profile of environmental benefits and annual program payments.

The standard contract offered to agents is obtained as follows. The standard penalty schedule p_t^0 in equation (2.24) equals the buffer installation cost-share payment plus all annual payments r received up until the date of early contract termination. Then, we find the minimum positive annual payment r_n^0 that satisfies the agent's participation condition in equation (2.25) under the standard penalty schedule numerically using Monte Carlo integration.

To account for the principal's cost of funding the program and the agent's opportunity cost of capital in real (inflation adjusted) terms, we use FSA's farm operating loan rate in April 2022, roughly 2.5%, as a baseline scenario. We also provide a robustness check on the simulation results using 5% as an alternative discount rate.

2.3.5 Simulated Contract Performance

Once the standard and optimal contract terms are derived for each parcel, the principal calculates enrollment costs, then chooses eligible parcels in descending order of their benefit-cost ratios as

shown in equation (2.31) until the specified budget is attained. As in the theoretical analysis, the principal must commit to spending its allotted budget as if all contracts are seen through to completion. To explore the sensitivity of differences in performance to program scale, we consider four different budget levels ranging from a low of $1 million to a high of $20 million. As is standard in PES programs, the environmental benefits obtained from each parcel are considered as independent projects that have no spillovers onto the environmental benefits obtained from nearby parcels, as is done in evaluating CRP projects using the EBI for each individual site.

The rate of contract non-completion represents the proportion of enrolled buffer acreage anticipated to be terminated before the contract reaches its expiration date. To calculate this, we obtain the parcel-level survival probability for each enrolled parcel in the program under the standard and optimal contracts. This survival probability is the joint product of the likelihood of maintaining the signed 10-year PES contract from time 1 to 9, as shown in equation (2.17). The resulting parcel-level survival probability is then multiplied by the parcel's program-eligible buffer acreage and aggregated across all enrolled parcels in the program. This sum provides the aggregated buffer acreage expected to complete the signed PES contract. The difference between the total enrolled and completed acreage yields the expected acreage that will be prematurely terminated before the contract expiration date.

2.4 Policy Simulation Results

In this section, we first compare quantitative differences in PES contract terms, including the penalty schedules and annual payment offered to agents, between the standard and optimal contracts. Then, we compare simulated policy outcomes, including (a) the rates of program participation and premature contract termination, (b) environmental benefits obtained, (c) total

program payments, (d) penalty revenue and (e) net program benefits at different program budget levels. Finally, we assess the robustness of our findings when the environmental benefits of individual PES projects are estimated with substantial uncertainty.

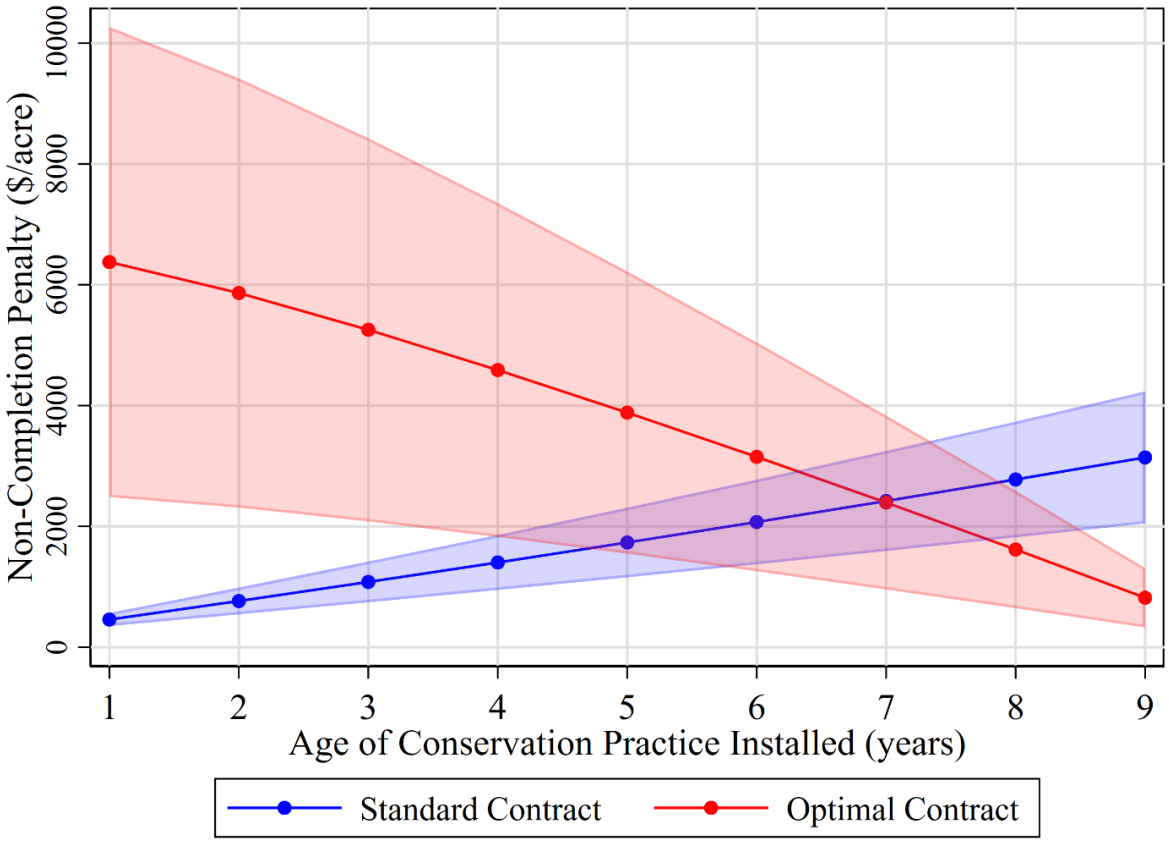
2.4.1 Contract Terms

We expect the optimal and standard penalty schedules to differ quantitatively in both level and trend because they have qualitatively different structures, as shown in equations (2.21) and (2.24) respectively. Figure 2.4 shows the average optimal and standard non-completion penalty schedules offered to the 7,223 agents, along with one standard deviation above and below the average. The two penalty schedules are markedly different in both level and trend. The average optimal penalty starts at a peak in the first year and decreases monotonically by over 85% during the contract period. In contrast, the average standard penalty offered starts at its lowest level, grows monotonically and reaches a maximum more than six times its initial value during the contract period. As a result, the optimal penalty is 13 times higher than the standard penalty initially but only about a fourth of the standard penalty at the end of the contract lifetime, on average. In addition, the magnitude of difference is substantial in most years. Consistent with Proposition 3, the two penalty schedules intersect only once, in year 7.

The magnitudes of the differences in the two penalty schedules provide an indication of how poorly the standard penalty structure manages the tradeoff between environmental benefits and foregone crop production income. The standard penalty is at its lowest when environmental benefits expected from the remaining contract periods are at their highest. Conversely, the standard penalty is at its highest when remaining environmental benefits are at their lowest. The standard penalty structure thus makes premature termination most attractive at times when remaining

environmental benefits are greatest. The optimal penalty schedule, in contrast, manages the tradeoff between environmental benefits and foregone crop production income in the most cost-effective manner possible.

Figure 2.4 Standard and optimal non-completion penalty schedules



Note: The graph presents the standard and optimal penalty schedules offered to 7,223 agents in the PES contract that converts cropland to grass buffer for a 10-year contract. Intervals represent one standard deviation from the mean.

The temporal structure of the optimal penalty, which is positively correlated with expected environmental benefits, means that it is better able to deter early contract termination than the standard penalty, which is negatively correlated with expected environmental benefits. That improvement in deterring early termination is substantial. Projects that are acceptable to the program (i.e., benefit-cost ratio greater than one) are on average 17 percentage points more likely

to be completed under the optimal contract than under the standard contract. A higher completion probability also means greater expected environmental benefits: Expected environmental benefits of acceptable projects under optimal contracts exceed those under standard contracts by an average of 19%. Finally, it is possible that a higher completion probability could mean a higher opportunity cost of participation and thus require offering a higher annual payment to ensure voluntary program participation. Annual payments under the optimal contract are in fact higher than those under the standard contract for most projects—but not all of them. For acceptable projects, annual payments under optimal contract terms exceed annual payments under standard contract terms by only 3% on average. Thus, the optimal contract structure achieves significantly better performance on a project-by-project basis at a modest increase in cost.

2.4.2 Contract Performance

This section compares the performance of optimal and standard contracts at the program level for a range of different budget levels. We first discuss differences in rates of program participation and premature contract termination. Thereafter, we compare the relative performance in total environmental benefits obtained, program expenditures, and penalty revenue under the optimal and standard contract structures.

Table 2.1 presents both program participation and premature contract termination rates for spending commitments (budget levels) ranging from small ($1 million) to large ($20 million). Participation rates are similar but lower under the optimal contract than under the standard contract, and this difference in participation rates rises as the program budget increases. Total buffer acreage enrolled is similar under the optimal and standard contracts with a budget of $1 million, but the participation rate is 1.1% lower under the optimal contract with a budget of $20

million. At the same time, premature contract termination rates are lower under the optimal contract than under the standard contract. This difference in premature termination rates also rises as program budget size increases because participation of parcels with higher opportunity costs of land (i.e., those with higher returns from opting out of the contract) increases at higher budget levels. As the budget level increases, the optimal and standard contract structures both enroll landowner parcels with higher opportunity costs; however, the standard contract has a much higher rate of contract non-completion. Specifically, premature termination rates in Table 2.1 are on average 3.7 percentage points lower under the optimal contract than under the standard contract for a budget of $1 million and 12.1 percentage points lower for a budget of $20 million.

Table 2.1 also shows the government's expected environmental benefits obtained, program costs, and penalty revenue under the standard and optimal contracts across different program budget levels. As expected, environmental benefits under the optimal contract are greater than those under the standard contract, with the difference in relative performance increasing as the program budget size increases. Environmental benefits are 3.7% greater under optimal contracts than under standard contracts for a budget of $1 million and 11.7% greater for a budget of $20 million. Expected program payments under the optimal contract also exceed those under the standard contract. Even though the budget commitments are identical, the lower non-completion rates under the optimal contract mean that actual program expenditures are greater. As with participation and contract termination rates, this difference in realized program expenditures rises as the budget size increases. Program expenditures are 3.9% higher under the optimal contract than under the standard contract with a budget of $1 million and 12.1% higher with a budget of $20 million. Overall, the increases in environmental benefits due to greater contract completion rates outweigh the increases in realized program payments, resulting in greater levels of net program

benefits under the optimal contract at each budget level. Additionally, these improvements in net program benefits under the optimal contract increase as program budget level is higher.

Table 2.2 provides important insights into how these differences arise. Table 2.2 categorizes parcels into four groups based on their program enrollment status under the optimal and standard contracts for the fixed budget at $10 million. These four groups on enrollment type include: (1) “Both”, representing parcels that would be enrolled under both optimal and standard contract structures; (2) “Optimal only”, representing parcels enrolled under the optimal but not standard contract; (3) “Standard only”, representing parcels enrolled under standard but not optimal contract; and (4) “Neither”, representing parcels that would not be enrolled in either contract structure.

Parcels enrolled under both optimal and standard contract structures (“Both”) are similar in terms of selecting parcels with high environmental benefits and low opportunity costs, as expected. While annual payments are slightly higher (1.3%) for these parcels under the optimal contract than under the standard contract, the completion rate on average is 8 percentage points higher and the average benefit-cost ratio is 6.4% higher. Parcels that are enrolled under the optimal contract only (“Optimal only”) have somewhat higher opportunity costs than the entire set of parcels but have much greater expected completion rates (20 percentage points) under the optimal contract than would be the case under the standard contract. These increases in the likelihood of contract completion lead to increases in expected environmental benefits that outweigh increases in annual payments needed to offset those higher opportunity costs (see equation 2.32), thereby increasing the benefit-cost ratios of these parcels under the optimal contract enough to make enrolling them desirable. In contrast, parcels enrolled only under the standard contract (“Standard only”) have lower opportunity costs, with correspondingly lower completion rates (7 percentage points lower)

Table 2.1 Simulation results for baseline scenario

Budget	Contract	Participation rate	Non-completion rate	Environmental benefits ($ million)	Program payments ($ million)	Penalty revenue ($ million)	Net program benefits ($ million)
$1M	Standard	2.2%	3.7%	10.5	1.0	0.0	9.5
	Optimal	2.2%	0.0%	10.9	1.0	-	9.9
$5M	Standard	8.6%	7.8%	36.6	4.6	0.1	32.1
	Optimal	8.0%	0.0%	39.5	5.0	-	34.5
$10M	Standard	15.5%	9.8%	64.4	9.1	0.2	55.5
	Optimal	14.8%	0.0%	70.5	10.0	-	60.5
$20M	Standard	28.0%	12.1%	111.1	17.8	0.6	93.8
	Optimal	26.9%	0.0%	124.1	20.0	-	104.1

Note: The table presents simulated outcomes of PES program that converts cropland into riparian grass buffer for a 10-year contract.

Table 2.2 Parcel characteristics by enrollment type

Enrollment Type	Annual crop return ($/acre)	Annual environmental benefits ($/acre)	Buffer acreage	Annual payment ($/acre)		Prob. of contract completion		Benefit-cost ratio		Num. parcels
				Standard	Optimal	Standard	Optimal	Standard	Optimal	
Both	157.5	1,475.8	3.8	172.9	175.2	92%	100%	7.8	8.3	1,232
Optimal only	283.1	1,932.3	4.9	291.8	300.8	80%	100%	5.1	6.0	61
Standard only	155.0	1,104.5	3.6	171.0	172.7	93%	100%	5.4	5.8	154
Neither	311.0	945.7	4.9	316.2	322.5	79%	92%	2.5	2.9	5,776
Total	281.3	1,047.9	4.7	288.5	294.0	81%	94%	3.5	3.9	7,223

Note: The table presents parcel characteristics in the baseline scenario in Table 2.1 with a fixed budget of $10 million. Parcels are categorized into four types based on program enrollment in the optimal and standard contracts: (1) "Both" represents parcels that would enroll under both optimal and standard contract structures; (2) "Optimal only" represents parcels enrolled under the optimal but not standard contract; (3) "Standard only" represents parcels enrolled under the standard but not optimal contract; and (4) "Neither" represents parcels not enrolled under either contract structure.

than would occur under the optimal contract. This decomposition for the four groups indicates that the superior performance of the optimal contract structure is due in part to its ability to enroll parcels that offer high environmental benefits but also high opportunity costs. When parcels have high opportunity costs, they are at high risk of premature contract termination under the standard contract. In contrast, the optimal penalty structure dramatically reduces noncompletion for these parcels with high environmental benefit and opportunity costs, making them more attractive for inclusion in the program.

Finally, consider the implication of a higher interest rate on the comparison of PES program outcomes between the standard and optimal contracts. A higher interest rate implies an increase in the government's cost of funding the program, as well as greater discounting of future program benefits and costs. One would thus expect the difference in future net program benefits between the optimal and standard contracts to fall as the interest rate rises. As expected, we find that the improvement in environmental benefits under the optimal contract is slightly reduced but remains substantial in the face of reasonable changes in the government's cost of funding the program (Table B1 in Appendix B). When the interest increases from 2.5% to 5%, the environmental benefits and program net benefits both remain higher under the optimal contract compared to the standard contract.

2.4.3 Sensitivity Analysis: Environmental Benefits with Uncertainty

The preceding analysis assumes that environmental benefits are known with certainty. In practice, however, the modeling used to estimate environmental benefits is often complex and may be based on information that is measured imprecisely, so that those estimates are subject to uncertainty. For

this reason, the design of USDA programs is more likely to use a proxy for environmental benefits, such as the EBI used to evaluate projects for the CRP.

In this section, we conduct sensitivity analysis to examine whether the gain in performance for the optimal contract is robust when the principal only has modeled environmental benefits that are uncertain (i.e., either overestimated or underestimated compared to actual environmental benefits). The key issue is whether the gains in switching from the standard to optimal contract are primarily due to (a) quantifying benefits correctly or (b) structuring the penalty correctly (i.e., higher penalties earlier in the contract and lower penalties as the contract approaches the expiration date). In this sensitivity analysis, the principal aims to maximize actual benefits for a fixed budget but uses the available modeled benefits with uncertainty when designing both standard and optimal contracts. The optimal penalty structure depends explicitly on environmental benefits with uncertainty (equation 2.21), while the standard penalty structure is based solely on past payments known with certainty and does not depend on environmental benefits (equation 2.24).

To operationalize this sensitivity analysis, we assume that "actual" environmental benefits B_{nt} are those calculated in our main baseline scenario in Table 2.1 using nutrient and sediment load reductions from the CBWM. First, we investigate the case when the modeled benefits $\hat{B}_{nt}$ overestimate the actual benefits, with random upward bias as much as 50%. Specifically, we use additive random error u_n for each parcel *n* drawn from a uniform distribution $U(0,1)$ as follows: $\hat{B}_{nt} = B_{nt}(1 + 0.5u_n)$. The principal then uses these overestimated benefits $\hat{B}_{nt}$ to (i) formulate the annual payment and penalties for premature contract termination and (ii) select which PES projects to fund given a fixed budget. The randomly drawn errors u_n change the ranking of benefit-cost ratios among individual PES projects, implying that different parcels may be selected into the program. Second, we similarly repeat this analysis for the case when the environmental benefits

are randomly biased downward as much as 50%, where we use the additive random error u_n as follows: $\hat{B}_{nt} = B_{nt}(1 - 0.5u_n)$.[21]

Table 2.3 reports the program performance under the optimal and standard contracts where modeled environmental benefits overestimate (Panel A) and underestimate (Panel B) the actual benefits. These results indicated that the relative performance improvements (i.e., actual benefits obtained) under the optimal contract remain consistently higher than the standard contract for both upward and downward biased modeled benefits. As in the baseline scenario in Table 2.1 (i.e., environmental benefits are known with certainty), the simulation results in Table 2.3 follow qualitatively similar trends when uncertainty and bias in modeled environmental benefits are examined for a range of fixed budget levels.

This sensitivity analysis suggests that the temporal structure of penalties for premature contract termination is the primary factor in the relative improvements in PES program performance under the optimal contract, despite uncertainty between modeled and actual environmental benefits. In other words, it is important to impose sufficiently high penalties in the early contract years to discourage early removal of established conservation practices and then decrease the penalty over time as anticipated environmental benefits diminish. In summary, the relative performance of the proposed optimal PES contract compared to the standard contract remains robust, with some degree of uncertainty in the modeled environmental benefits.

[21] We thank an anonymous reviewer for suggesting this sensitivity analysis.

Table 2.3 Simulation results: Sensitivity analysis using environmental benefits with uncertainty

Budget	Contract	Participation rate	Non-completion rate	Environmental benefits ($ million)		Program payments ($ million)	Penalty revenue ($ million)	Net program benefits ($ million)	
				Modeled	Actual			Modeled	Actual
Panel A: Modeled benefits overestimate actual benefits (biased upward)									
$1M	Standard	2.2%	4.2%	13.4	10.3	1.0	0.0	12.4	9.3
	Optimal	2.1%	0.0%	14.0	10.6	1.0	-	13.0	9.6
$5M	Standard	8.5%	8.0%	47.0	35.7	4.6	0.1	42.5	31.1
	Optimal	8.0%	0.0%	50.8	38.2	5.0	-	45.8	33.2
$10M	Standard	15.2%	10.2%	82.1	63.0	9.1	0.2	73.2	54.2
	Optimal	14.4%	0.0%	90.3	68.7	10.0	-	80.3	58.7
$20M	Standard	27.9%	12.2%	140.6	109.8	17.8	0.6	123.4	92.5
	Optimal	26.7%	0.0%	157.4	122.4	20.0	-	137.4	102.4
Panel B: Modeled benefits underestimate actual benefits (biased downward)									
$1M	Standard	2.2%	4.1%	8.5	10.1	1.0	0.0	7.6	9.1
	Optimal	2.1%	0.0%	8.9	10.5	1.0	-	7.9	9.5
$5M	Standard	8.2%	8.7%	29.6	34.6	4.6	0.1	25.1	30.1
	Optimal	7.8%	0.0%	32.2	37.0	5.0	-	27.2	32.0
$10M	Standard	15.0%	10.5%	51.4	61.6	9.0	0.3	42.6	52.8
	Optimal	14.3%	0.0%	56.7	67.2	10.0	-	46.7	57.2
$20M	Standard	27.6%	12.5%	86.9	107.8	17.8	0.6	69.7	90.6
	Optimal	26.5%	0.0%	97.5	119.7	20.0	0.0	77.5	99.7

Note: The baseline scenario in Table 2.1 assumes environment benefits are known with certainty. In Table 2.3, modeled environmental benefits are assumed to be known with uncertainty, where modeled benefits overestimate (Panel A) or underestimate (Panel B) the actual benefits (see section 2.3.2 for further details on methods).

2.5 Conclusion

PES programs have been widely implemented in the US and globally to enhance environmental benefits for water quality improvement, carbon sequestration, biodiversity, and environmental amenities to society more generally. Obtaining those environmental benefits often requires installation and long-term contracts to ensure vegetation growth in conservation practices. Thus, contract termination before the expiration date may significantly reduce expected net environmental benefits from PES contracts. The standard penalty structure for contract non-completion in PES programs in the US and several other countries requires participants to pay back most or all payments received plus interest and, possibly, fees. This paper is the first to examine the optimal non-completion penalty structure and annual payment in a multi-period PES program with general contract features.

Our theoretical analysis shows that the non-completion penalty structure under the optimal contract is fundamentally different from that under the standard contract. First, the optimal penalty is forward-looking and compensates for the principal's net benefits lost due to contract early termination, while the standard penalty is backward-looking and based on the program payments made in the past. As a result, the optimal penalty generally decreases over time while the standard penalty monotonically increases over time. Second, the optimal penalty structure decouples the penalty from total program payments received and increases flexibility in contract design. Finally, the optimal penalty generally increases the desirability of PES projects with high environmental benefits on parcels with high opportunity costs by improving the likelihood of contract completion.

Our numerical policy simulation considers a population of heterogeneous landowners whose cropland are eligible for a PES program that converts cropland to a conservation use designed to improve environmental benefits. The numerical policy simulation offers three key findings. First,

the optimal and standard penalty schedules are markedly different in both level and trend. On average, the optimal penalty monotonically decreases by over three-quarters, while the standard penalty increases monotonically and more than triples during the contract lifetime. Second, the optimal contract generally reduces the number of cropland acres converted for conservation purposes and enhances the performance of signed PES contracts instead, improving overall provision of environmental benefits given a fixed program budget. Third, improvements in performance of optimal contracts compared to standard contracts are often substantial and remain robust even with uncertainty in modeled estimates of environmental benefits from PES projects.

Our theoretical and numerical results together demonstrate the importance of decoupling penalties for non-performance from participation incentives. Our numerical results indicate that decoupling penalties for early termination from participation incentives has the potential to improve PES program performance substantially. PES programs like those in the conservation title of the Farm Bill have often struggled to meet participation goals. Frequently, those programs resort to increasing payments as a means of increasing participation. Under the standard penalty structure, any increase in the payment to encourage participation simultaneously increases penalties for non-performance, attenuating the effects of an increase in the payment level. The optimal penalty structure eliminates this problem.

Our analysis has several caveats and limitations. First, there are practical applicability issues since the optimal penalty structure explicitly depends on estimates of environmental benefits obtained from individual PES projects, which are often imprecise and subject to uncertainty. Our sensitivity analysis indicates that the relative improvements in program performance under the optimal contract structure remain robust in the presence of uncertainty in the estimated environmental benefits. Nonetheless, it requires substantial information to construct the model or

proxy to estimate environmental benefits, as done with the EBI for the CRP contracts, to maximize environmental benefits under either the optimal or standard contract designs.

Second, our model that compares the optimal and standard contract structures applies to environmental benefits that are flows, such as improvements in water quality that are experienced each year while conservation practices are in place. However, our model does not apply generally to environmental benefits from accumulated stocks, like sequestered carbon, that will be released back into the atmosphere once a PES contract terminates and the conservation practice is removed. Expanding the theoretical model and numerical policy analysis to deal with environmental benefits as stocks requires a different model structure and is thus beyond the scope of this paper. This distinction between flow and stock benefits is important to recognize, highlighting the need for further research on this topic regarding payment and penalty design for environmental benefits as stocks where past benefits may be lost after practice removal.

Third, our model assumes PES program managers treat environmental benefits from the conservation project on the parcel as additively separable from those of all other parcels. In some cases, there may be spatial spillovers of benefits from one parcel to other parcels located nearby. For example, habitat improvements for terrestrial or aquatic species on an individual parcel improve habitat connectivity for neighboring parcels. Incorporating spatial spillovers in environmental benefits is beyond the scope of analysis for this paper. Nonetheless, the intuitive expectation is that the optimal penalty will increase when incorporating spillovers, such as habitat quality, because the optimal penalty is a function of the environmental benefits for the individual parcel (as currently done), plus any additional environmental benefits from habitat connectivity on neighboring parcels. The standard penalty is unchanged since it only considers payments received and does not incorporate environmental benefits onsite or from neighboring parcels. Incorporating

spillovers such as these will generally increase expected environmental benefits in some locations relative to others, altering the optimal penalties for premature contract termination and, importantly, altering project benefit-cost rankings and thus optimal project selection.

While our analysis is framed in terms of a cropland retirement program like the CRP and CREP, the inferences we draw are applicable to a much broader array of conservation programs. Our analysis can be readily adapted in further research to encompass programs aimed at working farmland like EQIP, e.g., by modifying the structure of the agent's opportunity cost of participation. Since PES programs in several other countries feature contract structures much like the US conservation programs, our analysis can be readily adapted to other PES programs worldwide. Our analysis thus points to a way forward for improving the performance of a wide variety of PES programs.

Chapter 3. Emissions Trading Programs for Afforestation: Interactions with Federal Agricultural Conservation Programs

3.1 Introduction

Afforestation-based conservation practices in agriculture, such as establishing riparian forest buffers, provide both water quality and carbon sequestration benefits. To encourage agricultural landowners to adopt these practices, emissions trading programs have been promoted as a flexible and cost-effective solution for achieving pollution reduction goals (Weinberg and Claassen, 2006; Lankowski and Cattaneo, 2010; Shortle et al. 2012; Talberth et al. 2015). For instance, in water quality trading programs, agricultural conservation practices have been recognized as a low-cost supplier of nutrient emission reduction credits (Fisher-Vanden and Olmstead, 2013; Stephenson and Shabman, 2017). Similarly, the Biden-Harris Administration's Growing Climate Solutions Act of 2021 aimed to improve landowner access to carbon trading markets as a supplier of carbon offset credits derived from agricultural conservation practices. Despite these efforts, landowner participation in both water and carbon trading programs has been low (Fisher-Vanden and Olmstead, 2013; USDA, 2023).

Prior analyses on the performance of emission trading have paid little attention to its interaction with longstanding federal agricultural conservation programs. Federal agricultural conservation subsidy programs, authorized by quinquennial farm bills and administered by the U.S. Department of Agriculture (USDA), has been the primary source of subsidy payments for addressing pollution problems emanating from agriculture (Lichtenberg, 2017). The 2002 farm bill initiated an increase in subsidies for conservation programs on working farmland and spending on those programs has risen with every farm bill since (Stubbs, 2023). More recently, the Inflation Reduction Act of 2022

allocated an additional $19.5 billion to USDA conservation programs that pay for the adoption of agricultural conservation practices. Thus, emissions trading programs enter into a policy landscape where federal subsidy has been a primary source of funding for agricultural conservation, which could possibly reduce the efficiency of both programs due to increased adverse selection incentives (Fleming et al., 2020).

Emissions trading and agricultural conservation programs provide fundamentally different structures of payment. Agricultural conservation programs aimed at working farmland commonly pay for effort: Payment is based on the direct and implicit costs of installing conservation practices. Emissions trading pay for performance: Payment is based on the expected environmental benefits of conservation practice. For instance, payment increases with the modeled amount of nutrient runoff reduction or carbon sequestered by the installed conservation practice in the water quality or carbon trading programs. These two distinct incentive mechanisms likely compete, as landowners generally cannot receive payments from both federal conservation programs and trading markets simultaneously. In fact, the current water quality trading programs implemented in different regions in the United States typically have few transactions, as opposed to the robust participation and continuous expansion in federal conservation programs (Fisher-Vanden and Olmstead 2013; Shortle and Horan 2013; Savage and Ribaudo, 2016; Stubbs, 2023).

This paper provides an ex-ante analysis of the interactions between emissions trading programs and a major federal conservation subsidy program in promoting afforestation activities on agricultural land in the Chesapeake Bay region. We first examine the extent to which the federal conservation subsidy may have crowded out water trading programs. We then examine how stacking payments for carbon offsets with water quality trading payments would affect the

effectiveness and attractiveness of emissions trading program compared to the federal conservation subsidy incentives.

We begin with analyzing the supply of environmental benefits from agricultural parcels using a stated preference survey data from Lichtenberg et al. (2024), which conducted a discrete choice experiment (DCE) through an address-based survey of Maryland agricultural landowners. In the DCE, landowners who lack conservation cover in the riparian buffer zone are asked to make binary enrollment choices regarding buffer adoption under varying program attributes, including vegetation type (grass vs. forest), one-time upfront payment, recurring annual payments, delays in upfront payment, and contract length. Following Lichtenberg et al. (2024), we employ a standard logit model to examine landowner's program enrollment decision based on these program attributes and spatially explicit characteristics of landowner and farm operation collected in the survey.

We then simulate landowner's decision to establish riparian buffers on cropland in return for payments constructed based on features of three programs. First is USDA's Conservation Reserve Enhancement Program (CREP) that pays for effort by compensating landowners for the cost of adopting conservation practices. Second is the emissions trading programs that pays for performance based on the reduction of nutrient load or the amount of carbon sequestered by the established practice. Our numerical simulation uses an integrated assessment model that combines landowners' participation in each program with biophysical models of water quality and carbon sequestration benefits of riparian buffers to assess performance of these programs. We first compare performance of three payments independently, with each payment structure acting as the sole financial incentive to landowners for agricultural conservation. We then explore a scenario

where these payments provide competing incentives to landowners to examine how their interactions affect the program participation, environmental benefits, and program costs.

Our policy simulation uses an integrated assessment model that links landowner's stated program enrollment decision with parcel-specific environmental benefits in our numerical policy simulation. To measure water quality benefits of riparian buffers established on cropland, we estimate the reduction of nutrient runoff from crop field to the Chesapeake Bay using spatially-varying parameters from the Chesapeake Bay Watershed Model (CBWM) (Belt et al., 2014; Fleming et al. 2018). The CBWM is currently used by EPA and state governments to meet the total maximum daily loads (TMDL) requirements that mandate reduction in nutrient pollutant loads delivered to the Bay. To measure carbon sequestration benefits of established riparian buffers, we use newly available high-resolution forest carbon storage data in Maryland, which estimates the trajectory of carbon storage on newly established forest cover based on Ecosystem Demography Model (Ma. et al., 2021).

Our policy simulation provides several novel insights into the interaction between emissions trading programs and federal conservation programs aimed at afforestation activities on agricultural land. First, we find that water quality trading programs, when considered available in isolation, have the potential to provide sufficient financial incentives for landowners to engage in afforestation activities. Second, carbon payments are small in magnitude, compared to either CREP or water quality trading, and encourage very few landowners to establish riparian forest buffers. Third, in the scenario of CREP and emissions trading programs in competition, CREP's participation rate remains robust, while the water quality trading program's participation decreases substantially. Stacking water quality payments with payments for carbon sequestration has little effect on participation in trading programs. The federal conservation subsidies crowd out

incentives for participating in emissions trading programs that provide higher environmental benefits net of program payments in isolation (provided that both have similar transaction costs for participating). In addition, we find that competing sets of programs for the same agricultural conservation practice allow landowners to sort into the program with higher payments. Consequently, this leads to both programs achieving lower environmental benefits, net of program payments, compared to when each operates alone as the sole source of financial incentive for landowners.

Our study contributes to the literature on the evaluation of incentive schemes to promote the adoption of conservation practices in agriculture. Subsidy-based incentives have been criticized for its inefficiency as they do not necessarily target areas with higher environmental benefits (Babcock et al., 1997; Wu and Boggess, 1999) and they are subject to imperfect additionality (Lichtenberg 2021; Claassen et al. 2018; Fleming et al 2018; Mezzatesta et al., 2013; Lichtenberg and Smith-Ramirez 2011). As an alternative, emissions trading programs that pay for performance have been promoted as cost-effective approach to achieve pollution reduction (Lankowski and Cattaneo, 2010; Shortle et al. 2012; Rabotyagov et al. 2014). However, few prior studies have analyzed the effectiveness of emissions trading programs while accounting for their interactions with pre-existing agricultural conservation subsidy programs (Fleming et al., 2020). Our analysis suggests that the performance of pay-for-performance incentives in the emissions trading programs likely depends on the presence and generosity of pay-for-effort incentives in conservation subsidy programs. Our policy simulation is highly relevant to the current global efforts to achieve pollution reduction using competing payment schemes for the adoption of conservation practices.

The remainder of this paper proceeds as follows. Section 3.2 describes the stated preference study used to analyze the supply of riparian forest buffers from agricultural landowners. We

present an empirical framework to estimate landowner response to varying program attributes and discuss the econometric results from the stated preference study. Section 3.3 describes numerical policy simulation methods and policy scenarios of interest. Section 3.4 discusses policy simulation results. Section 3.5 concludes.

3.2 Stated Preference Study

In this section, we examine landowners' decision to establish riparian buffers on cropland under different program designs. In Section 3.2.1, we describe an empirical framework used to analyze stated preference survey data in Lichtenberg et al. (2024). In Section 3.2.2, we describe the survey design and implementation, and survey data. In Section 3.2.3, we discuss the result of standard logit estimation on landowner's program enrollment decision as a function of program attributes and characteristics of landowner and farm operation.

3.2.1 Empirical Framework

In the DCE, landowners make four binary choices between producing crops (i.e., status quo) and converting cropland into riparian buffers for T^0 years under a given riparian buffer program. Following Lichtenberg et al. (2024), we analyze each program enrollment decision independently relative to the status quo. Each landowner i faces a riparian buffer program j with different set of program attributes: one-time upfront payment net of adoption cost s_{ij}, recurring fixed annual payment r_{ij}, contract length of T_j, type of vegetation in the buffer θ_j, and d_j years of delay in payment timing for signing bonus payment. Suppose that the landowner i enrolls in the program j that requires establishment and maintenance of type θ_j riparian buffer for T_j years. Then, the landowner is obligated to install riparian buffers in return for upfront payment (net upfront

payment of s_{ij}), with d_j years of delay in payment timing. In addition, the landowner receives a series of fixed annual payment r_{ij} during the contract period.

The expected indirect utility of program j for landowner i is:

$$V_{ij} = \left(\beta_0 + \sum_{d_j>0} \beta_{d_j} \mathbb{1}\{D_j = d_j\}\right) s_{ij} + \left(\gamma_{T^0} + \sum_{\tau_j<T^0} \gamma_{\tau_j} \mathbb{1}\{T_j = \tau_j\}\right) r_{ij} \qquad (3.1)$$

$$+ X_i\psi + \kappa\theta_j + \alpha + \varepsilon_{ij},$$

where the baseline contract length is T^0 ($\tau_j < T^0$). The constant term α is the average status quo utility of landowners and ε_{ij} is an unobservable factor that affects landowner i's decision to enroll in the program j.

The coefficient β_0 represents the value of one-time net upfront payment without delays in payment timing for landowner's program enrollment decision. Then, the coefficient β_{d_j} represents how d_j years of delay in upfront payment timing affects landowner's program participation incentives. Delays in upfront payment may reduce landowner's participation incentive. For instance, PES programs generally offer payments to landowners after the verification of established conservation practice, which leads to delays in upfront payment and disincentivize landowners to adopt conservation practices.

The coefficient γ_{T^0} represents the value of annual payment r_{ij} in landowner's decision to enroll in the program j for T^0 years. The coefficient γ_{τ_j} captures potential variability in the value of annual payment stream with contract length T_j. Landowners may prefer a short-term contract to have a flexible land use option between cropland and conservation cover depending on crop market conditions. On the other hand, landowners may prefer a long-term contract to earn a stable flow of annual payment for a longer period of time.

The vector X_i includes characteristics of landowner and farm operation that affect landowner's program participation decision. For instance, the vector X_i includes landowner characteristics, such as age and education, participation experience with riparian buffer program, risk preference, and attitudes towards farm support programs. The vector also includes parcel characteristics such as property size, farm income share, and parcel-specific soil profitability of cropland in the riparian buffer area calculated using county-level soil rental rate from USDA National Agricultural Statistics Services (NASS), 1-meter resolution land use data from Chesapeake Conservancy, and National Commodity Crop Productivity Index from USDA Natural Resources Conservation Service (NRCS).

Assuming that the error term ε_{ij} follows an i.i.d. type 1 extreme value distribution, the probability of landowner i choosing program j in a given DCE scenario can be expressed using a standard form of logit probability:

$$P_{ij} = \frac{\exp(V_{ij})}{1 + \exp(V_{ij})}, \tag{3.2}$$

where V_{ij} denotes the utility associated with program j for landowner i in equation (3.1).

3.2.2 Survey Design and Implementation

The stated preference survey was developed in collaboration with regional experts and administrators of riparian buffer programs to analyze landowners' decisions to enroll in riparian buffer programs with varying program attributes discussed in the empirical framework. The DCE in the survey was modeled after the CREP, which represents the main funding source to incentivize riparian buffers on agricultural lands to improve water quality in the Chesapeake Bay. DCE questions were developed based on best practices outlined in Johnston et al. (2017). To enhance

consequentiality, the DCE has a two-alternative choice format where landowners choose between the proposed program and the status quo option (i.e., no enrollment in any program) instead of a three-alternative choice format (Johnston et al., 2017; Weng et al., 2021). To capture the preferences of individuals not currently enrolled in riparian buffer programs, the range of program payments is set to be higher than the currently available payments from CREP while keeping the range of payments offered within plausible bounds to ensure incentive compatibility (Vossler et al. 2023). Following the current minimum required by CREP in Maryland, the survey specifies a buffer width of 35 feet under the proposed program while installation and maintenance costs for riparian buffers were fully covered regardless of the buffer type.

In the DCE, each landowner was presented with four distinct choice scenarios, each requiring a binary (yes/no) response regarding their enrollment in a proposed program to adopt a riparian buffer on their farmland. The proposed programs comprised four key attributes: buffer type, a one-time upfront payment, a fixed recurring annual payment, and contract length. Table 3.1 presents a comprehensive list of these attributes with their possible levels in the DCE. The choice scenarios were constructed using a D-efficiency criterion that minimizes the standard errors of the estimated parameters in a logit specification (Scarpa and Rose 2008). Figure 3.1 provides an illustrative example of one of four DCE questions assigned to the landowner, outlining a program requiring the installation of a forest buffer. Landowners were explicitly instructed to treat each DCE question as an independent and non-additive decision.

The survey sampling focuses on agricultural parcels in Maryland tax assessor database, which provides spatially explicit parcel polygon data for all parcels. By spatially overlaying these parcels with the USGS National Hydrography Data, agricultural parcels intersecting or adjacent to relevant surface water bodies (e.g., streams, rivers, wetlands) for riparian buffer adoption were identified

Table 3.1 Descriptions of Program Attributes in a Discrete Choice Experiment

Program Attribute	Description
Vegetation type	Vegetation type of the riparian buffers: forest or grass
Upfront payment	One-time upfront bonus payment for program enrollment: $200, $500, $1,000, or $1,500 per acre
Annual payment	Recurring annual payments for a specified contract period: $100, $250, $500, or $750 per acre
Delays in upfront payment	Delays in the timing of upfront payment: 0, 2, or 5 years
Contract length	Number of years to maintain the established riparian buffers: 5, 10, or 15 years

and selected. The survey sample was further refined to include only parcels with at least 10 acres of major grain crops or other agricultural uses (e.g., hay, pasture, fruits, and vegetables) by analyzing 2020 USDA Cropland Data Layer. For these parcels, we mailed invitations to participate in an online survey, including a unique identification number to link the survey response to the parcel's geospatial information. For landowners with multiple parcels, we mailed an invitation to only one randomly chosen parcel they owned. This sampling process yielded 8,923 landowner parcels in Maryland. Establishing riparian buffers on these parcels is potentially eligible for payment from emissions trading programs and CREP as the federal conservation subsidy program.

The survey was conducted for these parcels between May and July 2021, using an online survey via Qualtrics with an option to request a paper copy of the survey. A total of 1530 landowner responses were received (1,420 online and 110 by mail), resulting in a response rate of 17%. DCE questions in our survey were intended for landowners who either lacked riparian buffers entirely or had buffers installed on only part of their riparian land, representing the focus group for potential program expansion. As a result, 538 respondents were asked at least one DCE question,

Figure 3.1 An Illustrative Example of a Discrete Choice Experiment Question

Would You Enroll?

Assume that **Program A** was offered as a possible program. Would you enroll in this program to install and maintain a riparian buffer on your property? If you choose "yes", we will ask you the length of the buffer (in feet) you would install under the chosen program.

Please remember that:

- Installation costs and maintenance costs will be fully covered by the program, regardless of the buffer type offered in the program
- You will receive the one-time bonus payment **at the time you enroll in the program**
- The program requires a minimum buffer width of 35 feet

Program element	**Program A**
Buffer type	Forest buffer
Bonus payment ($/acre)	$500
Annual payments ($/acre)	$250
Contract length (years)	15

The payment schedule for **Program A** will look like the following:

	Program A
Year 0 – Bonus payment ($/acre)	$500
Year 1 – Annual payment ($/acre)	$250
Year 2 – Annual payment ($/acre)	$250
Year 3 – Annual payment ($/acre)	$250
Year 4 – Annual payment ($/acre)	$250
Year 5 – Annual payment ($/acre)	$250
Year 6 – Annual payment ($/acre)	$250
Year 7 – Annual payment ($/acre)	$250
Year 8 – Annual payment ($/acre)	$250
Year 9 – Annual payment ($/acre)	$250
Year 10 – Annual payment ($/acre)	$250
	Contract ends

Would you enroll in **Program A**? (Choose one)

○ Yes – I would enroll

○ No – I would not enroll

leading to a total of 2,111 binary choices for establishing riparian buffers under a set of proposed program attributes.

Table 3.2 provides descriptive statistics of enrollment decisions and program attributes assigned in 2,111 DCE questions, and characteristics of 538 landowners and their farm operation. In the DCE, landowners stated a willingness to enroll in 35% of the proposed programs. The program attributes were randomly assigned across proposed programs in DCE. The survey also collected data on farm operation, prior experience with riparian buffer adoption and farm support programs, and characteristics of landowners, including risk preference and attitudes towards farm programs.

3.2.3 Estimation Results

Table 3.3 presents how program attributes affect the landowner's decision to establish riparian buffers on agricultural land. As in Lichtenberg et al. (2024), we find that payment type and levels were key determinants of riparian buffer adoption among other attributes. Higher upfront and annual payments significantly motivate participation. Delays in receiving upfront payments have small, statistically insignificant negative effects of stated participation. Contract length and vegetation type in the riparian buffer similarly have small, statistically insignificant impacts on stated willingness to participate.

A number of landowner and parcel characteristics also significantly affect participation in the riparian buffer program. Annual crop return serves as a proxy for the opportunity cost of land, as landowners are required to convert cropland in production to vegetative cover to provide ecosystem services. Thus, landowners with higher foregone annual crop return are more reluctant to engage in afforestation activities on agricultural land. We find that the estimated coefficient of foregone annual crop return is negative and statistically significant as expected.

Table 3.2 Description of Variables from the Survey and Summary Statistics

Variable	Description	Mean	S.D
Discrete choice experiment (2,111 choice observations)			
Enroll	A binary indicator for enrollment in a proposed program	0.35	0.48
Forest	A binary indicator for a riparian forest buffer	0.46	0.50
Grass	A binary indicator for a riparian grass buffer	0.54	0.50
Upfront	One-time upfront payment ($/acre in 1,000s)	0.84	0.48
Annual	Annual payment ($/acre in 1,000s)	0.41	0.25
Delay0	A binary indicator for no delay in upfront payment	0.33	0.47
Delay2	A binary indicator for 2 years delay in upfront payment	0.33	0.47
Delay5	A binary indicator for 5 years delay in upfront payment	0.35	0.48
Contract5	A binary indicator for 5-year contract	0.33	0.47
Contract10	A binary indicator for 10-year contract	0.34	0.47
Contract15	A binary indicator for 15-year contract	0.33	0.47
Landowner and farm characteristics (538 parcels)			
CropReturn	Calculated foregone annual crop income ($/acre in 1,000s)	0.28	0.14
CropArea	Cropland within a 35ft-width riparian buffer zone (acre)	2.26	2.21
PropertySize	Property size (acre)	88.7	73.8
FarmIncome	Share of household income from farming	0.15	0.27
Rent	A binary indicator for renting out any land within a parcel	0.50	0.50
Senior	A binary indicator for age over 65	0.56	0.50
College	A binary indicator for having a college degree or higher	0.61	0.49
RiskAverse	A binary indicator for being risk averse	0.27	0.45
Subsidy	A binary indicator for any payments for existing buffers	0.06	0.24
SelfFunder	A binary indicator for currently self-funding any buffers	0.28	0.45
FarmSupport	A binary indicator for participation in any farm support programs: crop/revenue insurance, livestock insurance, Farm Service Agency loans, dairy margin coverage or margin protection program, price support programs (commodity loans, loan deficiency payments, etc.)	0.23	0.42
NoPropMonitor	A binary indicator for agreement on the following statement: the government should not be allowed to come onto my property and monitor my farmland operations	0.61	0.49
NoTaxSupport	A binary indicator for agreement on the following statement: tax revenues should not be used for farm support programs	0.19	0.39

Note: The discrete choice experiment includes a total of 2111 choice observations from 538 parcels with characteristics or landowner and parcels. Foregone annual crop return is approximated using national commodity crop productivity index and cash rental rate for non-irrigated cropland following Kim et al. (2024).

Table 3.3 Logit Estimation for Enrollment in Riparian Buffer Program: Discrete Choice Experiment

Variable	**Dep. Var. Enroll = 1**	
Program attributes	Coef.	S.E.
Upfront payment (baseline: no delay)	0.27*	(0.13)
Upfront payment × 2-year delay	-0.10	(0.13)
Upfront payment × 5-year delay	-0.11	(0.12)
Annual payment (baseline: 15-year contract)	0.85***	(0.25)
Annual payment × 5-year contract	-0.11	(0.26)
Annual payment × 10-year contract	0.21	(0.24)
Forest buffer (baseline: grass buffer)	-0.13	(0.10)
Landowner and parcel characteristics		
Crop Return	-1.29***	(0.37)
Farm Income	-0.43*	(0.22)
Farm Support	-0.34*	(0.14)
Rent	0.24*	(0.11)
Senior	-0.69***	(0.10)
College	0.14	(0.11)
Risk Averse	-0.78***	(0.12)
Subsidy	0.79***	(0.21)
Self-Funder	0.68***	(0.11)
No Prop Monitor	-0.68***	(0.10)
No Tax Support	-0.27*	(0.14)
Constant	0.04	(0.22)
Number of observations: 2,111 choice observations from 538 parcels		

Note: In addition to variables shown above, the estimation includes binary indicators for parcels with missing characteristics and the results with these variables are available in Appendix A.

p-value * < 0.05, ** <0.01, *** 0.001

Existing studies suggest mixed evidence on how land tenure affects conservation practice adoption which requires upfront investment for long-term benefits (Lichtenberg, 2007). Landowners who rent out their agricultural land do not conduct farming operations on that land themselves. These landlords are more willing to invest in riparian buffers, likely because doing so protects the value of their agricultural land over the long run from soil erosion.

On the other hand, owner-operators who are heavily engaged in farm operation may have concerns about establishing conservation cover due to its potential interference with farm operation such as crop damage due to wildlife. We find that landowners who participated in the farm support programs and whose income mainly consists of farm income are less willing to enroll in the conservation program that requires conversion of cropland into conservation cover and monitoring activities on their farm operations.

Landowner's age may affect the conservation practice adoption. Older landowner nearing retirement may be reluctant to sign a long-term contract that reduces the flexibility of land use Their shorter time horizons may reduce the long-term benefits of conservation measures sufficiently to make them not worthwhile personally. And the restrictions on use of the land from signing long term contracts may reduce the sale value of the land. As expected, we find that the coefficient of landowner's age being greater than 65 is negative and statistically significant.

Landowners' risk preference may affect their decisions to establish a new conservation cover on agricultural land in return for program payments because establishing riparian buffers on cropland may affect the variability of farm income. Riparian buffers can increase or decrease farm income variability. On the one hand, long term conservation contracts provide a stable source of income that reduces year-to-year variability in farm income. On the other hand, buffers may harbor pests, weed seed banks, and crop diseases that can cause damage. They may also interfere with

current farm operations, increasing production. We find that risk-averse landowners are less willing to enroll in a conservation program, suggesting that perceived negative effects outweigh any positive effect of stabilizing income.

Current enrollees who currently receive program payments for established conservation cover may be more willing to establish additional conservation cover because they may have lower transaction costs for program enrollment and low opportunity cost of land, compared to those who have not participated in the program, holding else constant. Similarly, landowners who have adopted conservation practice without payment previously could be more likely to enroll in the program to receive payments. These landowners are likely to lower costs of establishing riparian buffers compared to private benefits, such as erosion control and crop protection. We find that the estimated coefficients for landowners who currently receive any subsidy for existing riparian buffers and those who have self-funded riparian buffers are positive and statistically significant.

Finally, we find that landowners who dislike government monitoring of their operations (required to ensure compliance with contracts) are less likely to enroll in a conservation program, as are landowners who oppose the use of tax revenues for farm support programs. Under standard economic logic ("everyone has a price"), these results suggest that landowners with such preferences have reservation prices well above any of the payments offered in the DCE, suggesting that they are out of reach for any reasonable program.

3.3 Policy Simulation

We conduct a numerical policy simulation to evaluate the performance of emissions trading programs and the federal agricultural conservation program. In Section 3.3.1, we explain the methodology used to calculate water quality and carbon sequestration benefits of riparian forest

buffers using social cost metrics for nutrient loads and carbon. For water quality benefits, we use the CBWM parameters to estimate reductions in nitrogen (N) and phosphorus (P) runoff when converting cropland into riparian forest buffers, and then value these benefits based on the social costs of the pollutants. For carbon sequestration benefits, we use high-resolution data on carbon storage growth of established forest buffers and value these benefits using the social cost of carbon adjusted for the contract period.

In Section 3.3.2, we explain three different structures for upfront and annual payments designed to establish riparian forest buffers, based on two primary types of programs. The first type is the federal agricultural conservation program, specifically the USDA's CREP. This program provides financial support to landowners by subsidizing the initial costs of establishing riparian buffers and offering recurring annual payments throughout the contract period. The second type consists of emissions trading programs, which include both the water quality trading program and the carbon trading program. In these programs, landowners receive payments based on the environmental benefits provided by the riparian forest buffers, specifically the improvements in water quality and carbon sequestration during the contract period valued at market prices. By comparing these payment structures, we aim to understand how different payment schemes influence the program performance.

In Section 3.3.3, we provide simulation method used to evaluate the performance of each program both in isolation and with potential interactions between them. In the former scenario, the two types of programs are evaluated separately as the sole financial incentives for landowners to adopt conservation practices on their agricultural land. In the latter scenario, landowners can choose one type of program to receive payments for adopting conservation practices (enrollment in both programs simultaneously is not permitted). We use the estimated landowner responses to

program attributes from the stated preference study to simulate the likelihood of program enrollment under different payment structures. We then build an integrated assessment model to combine individual landowner program enrollment decisions with environmental benefits. Simulation outcomes of interest are program participation rates, environmental benefits, and program costs over the contract period.

Our simulation focuses on 538 landowners who participated in the DCE. These landowners either did not have any conservation cover on their riparian buffer zones or had established riparian buffers for only a portion of their stream frontage. Therefore, our simulation is directly relevant to the current political efforts to offer both market- and subsidy-based financial incentives to increase the adoption of land conservation practices.

3.3.1 Environmental benefits

Riparian buffers provide numerous ecosystem services, such as reducing nutrient runoff, sequestering carbon, enhancing wildlife habitat and aquatic ecosystems, and mitigating stream bank erosion (Belt et al., 2014; Sweeney and Newbold, 2014). In this analysis, we estimate downstream water quality benefits and carbon sequestration benefits of the established riparian forest buffers, which are the two benefits that are eligible for payments from emissions trading programs. Installing riparian buffers is a key component of plans to meet agricultural commitments for reducing nutrient and sediment loads into the Chesapeake Bay under TMDL, which is a regulatory framework established by the EPA to limit specific pollutants that water bodies can receive while still meeting water quality standards. The physical estimates of nutrient load reduction and carbon sequestered by riparian buffers serve two purposes in our analysis. First, we monetize the parcel-specific environmental benefits using the social cost of nutrient loads to the

Chesapeake Bay and the social cost of carbon. Second, we calculate the amount of emission offset credits generated from each parcel, which is then converted to payments offered by the emissions trading programs in Section 3.3.2.

3.3.1.1 Water Quality Benefits

To calculate water quality benefits of riparian buffers, we follow Kim et al. (2024) to estimate the time profile of N and P runoff reduced by converting cropland into riparian buffers using parameters from the CBWM. The CBWM has been used by EPA and Bay states to evaluate the impact of conservation practices on nutrient reductions to meet Chesapeake Bay TMDL. Recent studies have also used these parameters to estimate the environmental benefits of conservation programs and assess the cost-effectiveness of various policy scenarios (Talberth et al., 2015; Fleming et al., 2018; Fleming et al., 2020). The CBWM allows for modeling and assessment of these impacts at a localized geographical scope. For instance, the model parameters include county-level pollutant loads by land use, nutrient runoff removal rate of riparian buffers across hydrogeomorphic regions, and delivery ratio of pollutant load from the nearest edge of the stream to the Bay across land-river segments that is smaller than the USGS's 8-digit Hydrologic Unit Code. These spatially explicit data on water quality benefits of riparian buffers are then overlaid with each parcel's riparian buffer area identified using high resolution (1-meter) land use and land cover data developed by the Chesapeake Conservancy.

The establishment of riparian buffers on cropland leads to both direct and indirect water quality improvements. Direct benefits stem from the immediate reduction in pollutant loads as cropland, which generally has higher fertilizer use and soil erosion, is converted to forest buffers. These direct reductions in pollutants persist throughout the contract period and vary depending on the

specific county and land-river segment where the buffers are established. Indirect benefits include the decreased pollutant loads as the established riparian buffers filter nutrient and sediment runoff from adjacent cropland before they reach nearby streams and rivers. These benefits grow over time as the buffer matures and removes greater amount of pollutant loads (Hairston-Strang, 2005; Simpson and Weammert, 2009; Belt et al., 2014).

Let q_{it}^{z} denote represent the expected annual reduction in pounds of pollutant z (where z can be either N or P) achieved per acre of riparian forest buffers established on parcel i. This reduction comprises both direct and indirect pollutant load reductions and can be expressed as:

$$q_{it}^{z} = \underbrace{\left(d_{i,crop}^{z}\alpha_{i,crop}^{z} - d_{i,forest}^{z}\alpha_{i,forest}^{z}\right)}_{direct\ reduction} + \underbrace{\alpha_{i,crop}^{z}x^{z}\psi_{it}^{z}d_{i,crop}^{z}}_{indirect\ reduction}. \quad (3.3)$$

The first bracket is the direct reduction of pollutant load, estimated by the difference in pollutant loads between forest cover and cropland. The coefficients $\alpha_{i,crop}^{z}$ and $\alpha_{i,forest}^{z}$ are the per-acre loads of pollutant z from cropland and forest cover measured at the edge of the nearest stream for parcel i. The parameter $d_{i,crop}^{z}$ and $d_{i,forest}^{z}$ are delivery ratio factors to account for attenuation occurring while the pollutant loads are transported from the landowner's cropland and riparian forest buffers, respectively, to the Chesapeake Bay.

The second term is the indirect reduction of pollutant load, that is, the amount of pollutant load from adjacent cropland treated by an acre of installed riparian buffer, which equals the product of four parameters: 1) pollutant loads from an acre of cropland, α_{crop}^{z}, 2) the ratio of neighboring cropland acres to buffer acres for which the efficiency rate applies, x^{z}, 3) the proportion of pollutant loads removed by an acre of t-year-old forest buffer on parcel i, ψ_{it}^{z}, known as the practice efficiency rate, and 4) the delivery ratio of pollutant from crop field to the Bay, $d_{i,crop}^{z}$.

Finally, we obtain the social benefits of both direct and indirect reductions in N and P using the social cost per pound of each pollutant m^z: \$17.11 for N, \$207.66 for P in 2021 value (Choi et al., 2020). Thus, the present value of expected water quality benefits B_i^{water} for an acre of riparian forest buffers established in each parcel i during the contract period T is then:

$$B_i^{water} = \sum_{t=0}^{T-1} \sum_{z=N,P} q_{it}^z \, m^z \delta^t, \tag{3.4}$$

where δ^t is a discount factor.

3.3.1.2 Carbon Sequestration Benefits

To calculate carbon sequestration benefits, we obtain high-resolution raster data on the trajectory of carbon storage growth for newly established forest cover on bare ground generated by Ecosystem Demography Model (Ma et al., 2021; 2022a; 2022b). The model incorporates spatial and temporal variation in weather conditions (temperature, precipitation, etc.), soil characteristics (depth, water retention, etc.), and atmospheric CO2 concentrations to estimate forest aboveground biomass. Thus, the model provides localized estimates of carbon storage densities of forest in kilograms of carbon per square meter (kg C/m²) for each 30m by 30m grid cell, covering most of the northeastern United States, including Maryland. This carbon raster data set is then overlaid with agricultural land within 35-feet riparian buffer area in each parcel to construct the time profile of the amount of carbon sequestered by riparian forest buffers newly established on cropland. We first calculate the arithmetic mean of the carbon storage densities in each grid cell for the riparian buffer area. We then repeat the same process for each year in the raster data, yielding year-specific trajectory of aboveground biomass storage density estimates for each parcel (see Appendix C for a detailed description of methods).

Let q_{it}^{C} denote the expected metric tons of carbon sequestered by the newly established forest cover on parcel i in each period t. To monetize the environmental benefits of carbon sequestration, we use the social cost of carbon, m^{C}. We first convert the latest estimates of the social cost of carbon, \$120/metric ton CO2, from Carleton and Greenstone (2022) and the EPA (2023), using the carbon-to-CO2 molecular ratios, yielding \$460.72 per metric ton of carbon in 2021 values. Standard social cost of carbon estimate accounts for economic damage occurring many years into the future while we consider the benefits of keeping carbon out of the atmosphere for relatively short-term contract period T. Therefore, we adjust the social cost of carbon downwards to account for the potential removal of forest cover by landowners after the contract ends. As a baseline, we adjust the social cost of carbon to account for a 15-year contract using an exponential decay function, which yields \$144.07 per metric ton of carbon.

Finally, the present value of carbon sequestration benefits of establishing and maintaining forest cover on cropland in parcel i for T years is:

$$B_i^{carbon} = \sum_{t=0}^{T-1} \sum_{z=N,P} q_{it}^{C} \, m^{c} \delta^{t}. \tag{3.5}$$

3.3.2 Program Types and Attributes

Our simulation considers three distinct programs to construct different payment structures offered to landowners for establishing riparian forest buffers on agricultural land: CREP, water quality trading program, and carbon trading program. We evaluate these programs both in isolation and in competition. For all programs, we consider 15-year contract that establishes and maintains riparian forest buffers in return for payment without delays in payment timing. The stated preference study above indicates two significant factors influencing landowner enrollment

decisions: payment type and level. As a baseline scenario, we focus on the differences in one-time upfront payment and recurring annual payments among these programs, holding other program attributes the same.

3.3.2.1 Conservation Reserve Enhancement Program

Established in 1997, the CREP is a collaborative federal-state initiative designed to encourage landowners to adopt conservation practices on their agricultural land, particularly in areas susceptible to environmental degradation. In the Chesapeake Bay region, CREP is the primary funding source for the installation of riparian buffers, which are vegetated areas along waterways designed to mitigate erosion, reduce nutrient runoff, and improve water quality. CREP plays a crucial role in meeting TMDL requirements in the Chesapeake Bay watershed. Agricultural nutrient runoff is a significant contributor to water pollution in the Chesapeake Bay watershed, impacting water quality and ecosystem health. CREP supports TMDL goals by incentivizing landowners to establish riparian buffers and other conservation practices that reduce nutrient runoff from agricultural lands into waterways leading to the Chesapeake Bay.

Landowners who enroll in CREP agree to convert portions of their cropland in riparian zones into forests while maintaining agricultural activities elsewhere on their property. The program typically operates under a 15-year contract for riparian forest buffers, during which landowners commit to maintaining the established conservation practices. In return, they receive a cost-share payment that fully covers installation expenses and annual rental payments for the land set aside for conservation.

CREP in the Chesapeake Bay watershed cost-shares the installation of riparian forest buffers. Let c_i denote the parcel-specific cost of adopting riparian forest buffers and η^{CREP} denote CREP's

cost-share rate for the cost of installing riparian forest buffers. Following the current CREP in Maryland, CREP fully covers installation expenses for riparian forest buffers, where the State of Maryland adds its own 50% cost share to the 50% provided by USDA ($\eta^{CREP} = 1$). Let s_i^{CREP} denote the per-acre one-time upfront payment net of practice adoption cost under CREP for landowner i:

$$s_i^{CREP} = -(1 - \eta^{CREP})c_i^{forest} = 0. \tag{3.6}$$

Let r_i^{CREP} denote the recurring annual payment per acre of riparian forest buffers during the T-year contract period under CREP for parcel i. We follow the USDA Farm Service Agency's general procedure to calculate CREP annual payment for each parcel. Annual payment per acre of riparian buffers equals the soil rental rate of parcel i, μ_i, multiplied by incentive rate λ as follows:

$$r_i^{CREP} = \lambda\mu_i. \tag{3.7}$$

Maryland's CREP incentive rate for riparian forest buffers is set at three ($\lambda = 3$). The parcel-specific soil rental rate (μ_i) is determined by the county-level soil rental rates for non-irrigated cropland from the USDA's NASS, adjusted for parcel-specific soil productivity in the riparian buffer area as measured by the National Commodity Crop Productivity Index from the USDA's NRCS. Our survey respondents were selected from a unique address-based sample, enabling us to estimate parcel-specific soil rental rates based on the distinct soil types present in each parcel's riparian buffer area. This high level of detail in modeling CREP incentives and environmental benefits allows for a more precise evaluation of the program's performance than previously possible. On average, the annual payment for converting cropland within a 35-foot riparian buffer zone into forest buffers is $231.05 per acre, with a standard deviation of $91.42 per acre.

3.3.2.2 Water Quality Trading Program

Water quality trading program is a market-based approach to improve water quality by allowing point source polluters, such as wastewater treatment plants, subject to pollution reduction requirements to meet their obligations by purchasing credits from other entities that have exceeded their reduction targets. In water quality trading program, agricultural operations can generate nutrient offset credits by implementing agricultural conservation practices that reduce N and P runoff, such as cover crops and riparian buffers, and then sell these credits to wastewater treatment plants or other entities that are required to offset their N and P loads to comply with regulatory requirements (Ribaudo and Shortle, 2019). The offset credits obtained from nonpoint source such as agricultural sector are subject to uncertainty in achieving water quality benefits and thus discounted when they are traded to offset pollutant loads from point source (Malik et al. 1993; Lankoski and Cattaneo 2010; Fisher-Vanden and Olmstead 2013).

In general, water quality trading programs do not provide either one-time signing bonus payment or cost-share payment to subsidize the cost of adopting conservation practices ($\eta^{WQT} = 0$):

$$s_i^{WQT} = -(1 - \eta^{WQT}) c_i^{forest} = -c_i^{forest}. \quad (3.8)$$

Because parcel-specific cost of establishing riparian forest buffers is not available, we use the average installation cost of riparian forest buffers in Maryland, which equals $2,185.60/acre in 2021 value, ($c_i^{forest} = 2185.60$) (Price and Wainger, 2019).

Let r_i^{WQT} denote the expected annual payment from the water quality trading program for establishing and maintaining riparian forest buffers on parcel i during time T. Following the constant annual payments in the stated preference survey, we construct a schedule of constant annual payment from the water quality trading program based on the average reduction of N and

P loads during the contact period T. We first obtain the average pound of annual pollutant loads reduced by an acre of riparian forest buffers established on parcel i during the contract period, $\bar{q}_i^z$ (i.e., average of q_{it}^z in equation 3.3). We then multiply this average reduction by (i) per-pound price of N and P load offsets in the water quality trading programs, p_i^N and p_i^P, and (ii) the trading ratio between nonpoint and point source pollutant loads, ϕ:

$$r_i^{WQT} = \phi \sum_{z=N,P} \bar{q}_i^z p^z \tag{3.9}$$

To obtain $\bar{q}_i^z$, we follow the same calculation to obtain q_{it}^z in equation (3.3). For the price of N and P load offsets (p_i^N and p_i^P), the current water quality trading program in Maryland does not publish transactions with offset credit prices for per pound of N and P loads. Thus, as a baseline scenario, we assume that landowners receive the abatement costs of N and P loads for wastewater treatment plants by upgrading facilities, which equals $20 per pound for N and $106 per pound for P ($p^N = 20$ and $p^P = 106$) (Jones et al. 2010). For the trading ratio between nonpoint source (agriculture) and point source (wastewater treatment plants) nutrient emissions reduction in the trading market, we use 2:1 ($\phi = 0.5$) as a baseline following Maryland's trading and offset policy guideline (MDE 2017). The resulting average annual payment from water quality trading equals $487.19/acre on average across 538 parcels with a standard deviation of $182.68/acre.

3.3.2.3 Carbon Trading Program

Establishing forest cover on agricultural land sequesters carbon from the atmosphere and landowners can potentially obtain carbon emissions offset credits by restoring riparian forest buffers and sell those to the power sector under regulatory requirements on carbon emissions reduction. The Regional Greenhouse Gas Initiative (RGGI) is a market-based cap-and-trading program in the northeastern United States to cap and reduce greenhouse gas emissions from the

power sector. The participating states in RGGI include Maryland, Delaware, Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont (Virginia ceased its participation in 2023). Under RGGI, participating states issue a fixed number of allowances, each representing the right to emit one ton of CO2. Power plants covered by RGGI must hold allowances to cover their emissions, either through allocation from the state or through purchasing allowances at auction. While the RGGI market primarily focuses on regulating emissions from power plants, it allows for the inclusion of offset projects from other sectors, such as agriculture, to help achieve overall emission reduction goals.

We assume that landowners receive payments based on the expected increase in carbon storage when converting cropland to forest cover, assuming that the parcel initially in cropland has a baseline carbon storage set to zero. In general, the carbon trading program does not provide one-time signing up payment for program participation or cost-share payment to subsidize the installation cost of agricultural conservation practices that sequester carbon ($\eta^{Carbon} = 0$):

$$s_i^{Carbon} = -(1 - \eta^{Carbon}) c_i^{forest} = -c_i^{forest}.$$

Similar to the water quality trading program, we construct a fixed schedule of constant annual payment based on carbon sequestration benefits. Let r_i^{Carbon} denote the expected annual payment from the carbon trading program for establishing riparian forest buffers on parcel i. We obtain r_i^{Carbon} based on the product of (i) the average of annual metric tons of carbon sequestered by the newly established forest cover on parcel i, $\bar{q}_i^C$, which is the average of q_{it}^C in equation (3.5), and (ii) the price of carbon offset credits per metric ton of carbon p^C:

$$r_i^{Carbon} = \bar{q}_i^C p^C, \tag{3.10}$$

where we obtain p^C from the average price of offset credits in RGGI's 2021 auctions, which is $38/mt of carbon.

3.3.3 Policy Simulation Method

Given the net upfront payment s_{ij} and annual payment r_{ij} offered to landowner i from program j, we estimate the landowner i's probability of enrollment in program j, $\hat{P}_{ij}$, using equations (3.1) and (3.2). We then calculate the expected enrolled acres for each parcel i under program j, which is the product of the estimated probability of program enrollment $\hat{P}_{ij}$ and each parcel's 35-feet riparian buffer area. Aggregating the parcel-specific expected enrolled acres provides the overall participation rate in each program. In addition, the expected enrolled acres are combined with parcel-specific environmental benefits and program payments to calculate the total environmental benefits and program expenditure.

3.3.3.1 Probability of Program Enrollment

Suppose program j is the only source of payments (s_{ij}, r_{ij}) for landowner i for the adoption of riparian forest buffers. The landowner compares the utility from the status quo to that from program j to decide whether to enroll in the program. To measure landowner's decision to enroll, we estimate the likelihood of landowner i enrolling in program j:

$$\hat{P}_{ij} = \frac{\exp\left(\hat{V}_{ij}\left(s_{ij}, r_{ij}, X_i\right)\right)}{1 + \exp\left(\hat{V}_{ij}\left(s_{ij}, r_{ij}, X_i\right)\right)}, \tag{3.11}$$

where the indirect utility $\hat{V}_{ij}(s_{ij}, r_{ij}, X_i)$ is estimated based on the logit model with program payments s_{ij} and r_{ij} in equation (3.1), holding other program attributes constant. Thus, the estimated probability of program enrollment $\hat{P}_{ij}$ varies across program j due to varying program payments (s_{ij}, r_{ij}) and varies across landowners due to characteristics of the landowner and parcel X_i.

Consider now that there are two programs, j and k, that offer different sets of payments, (s_{ij}, r_{ij}) and (s_{ik}, r_{ik}) for the adoption of riparian forest buffers. The landowner is not allowed to enroll in both programs and must choose one program to enroll. As the landowners make a binary choice of program enrollment in the stated preference survey, we assume that the landowner compares utility from each program $V_{ij}(s_{ij}, r_{ij}, X_i)$ and $V_{ik}(s_{ik}, r_{ik}, X_i)$ and compares the status quo utility and the utility from enrollment in the program that provides higher utility. In other words, if program j offers higher utility than k, then the landowner's estimated probability of installing riparian forest buffers is obtained from program j:

$$\hat{P}_{ik} = 0 \quad and \quad \hat{P}_{ij} > 0 \quad if \quad \hat{V}_{ij}(s_{ij}, r_{ij}, X_i) > \hat{V}_{ik}(s_{ik}, r_{ik}, X_i) \quad \forall j \neq k. \tag{3.12}$$

The program type that yields the higher indirect utility for landowner i varies across landowners depending on the landowner and parcel characteristics, and program payments offered to each landowner.

Payments for ecosystem services may not provide additional environmental benefits if landowners would have adopted the practice in the absence of the program payment. Thus, we account for additionality of payments by focusing on the increase in the probability of practice adoption for landowner i induced by the program payment. Let $\hat{P}_{ij}^0$ denote the estimated probability of program enrollment for landowner i without cost-share payment and recurring annual payment from program j, holding other program attributes constant:

$$\hat{P}_{ij}^0 = \frac{\exp\left(\hat{V}_{ij}(s_{ij} = -c_i^{forest}, r_{ij} = 0, X_i)\right)}{1 + \exp\left(\hat{V}_{ij}(s_{ij} = -c_i^{forest}, r_{ij} = 0, X_i)\right)}. \tag{3.13}$$

Then, the increase in the probability of practice adoption for landowner i attributed to payments from program j is:

$$\hat{P}_{ij} - \hat{P}_{ij}^0. \tag{3.14}$$

3.3.3.2 Simulation Outcomes

Simulation outcomes of interest include program participation rate, environmental benefits, and program costs. We first obtain the expected number of acres enrolled under program k for each landowner i, which is a product of the program-eligible acres in landowner i's parcel, l_i, and the estimated additional probability that landowner establish conservation cover under program j:

$$\left(\hat{P}_{ij} - \hat{P}_{ij}^{0}\right) l_i \tag{3.15}$$

Then, participation rate of the program k is then the ratio of expected enrolled acres to total program eligible acres across parcels:

$$\frac{\sum_i \left(\hat{P}_{ij} - \hat{P}_{ij}^{0}\right) l_i}{\sum_i l_i}. \tag{3.16}$$

Similarly, we calculate the environmental benefits of conservation practice established by the program. Using the net present value of water quality and carbon sequestration benefits B_i^{water} and B_i^{carbon} obtained in the previous section, the present value of total environmental benefits obtained from across parcels enrolled in the program k's contract period T is:

$$\sum_i \left(\hat{P}_{ij} - \hat{P}_{ij}^{0}\right) l_i \left(B_i^{water} + B_i^{carbon}\right). \tag{3.17}$$

Finally, we calculate the program costs based on the present value of payments offered to landowner i in return for establishing conservation cover under program j. Then the present value of total program costs across landowners is:

$$\sum_i \left(\hat{P}_{ij} - \hat{P}_{ik}^{0}\right) l_i \left[s_{ij} + \sum_{t=0}^{T_j - 1} \delta^t r_{ij} \right]. \tag{3.18}$$

To calculate the confidence intervals for policy simulation outcomes, we employ the Krinsky and Robb (1986) method, which has been widely used in existing studies to estimate the range of

outcomes for land use transitions (Lewis 2010; Lewis et al. 2011). First, we construct a multivariate normal distribution of the model parameters from equation (3.1), utilizing the logit estimated parameters presented in Table 3.3 and the corresponding covariance matrix. Next, we draw multiple vectors of model parameters from this multivariate normal distribution. For each drawn vector, we compute the parcel-specific predicted probability of enrollment in program jjj and derive the related simulation outcomes, such as participation rate, environmental benefits, and program expenditure. Finally, by constructing the empirical distribution of these outcomes, we estimate the confidence intervals for the program outcomes.

3.4 Policy Simulation Results

This section evaluates the performance of CREP, the water quality trading program, and the carbon trading program, focusing on participation rates (Equation 3.16), environmental benefits (Equation 3.17), and program costs (Equation 3.18). We first compare the payments offered for establishing riparian forest buffers under each program. Next, we present simulated policy outcomes under scenarios where each program is the sole payment option for landowners adopting riparian forest buffers. We also examine a scenario where both the federal agricultural conservation subsidy program and the water quality trading program offer competing incentives. Finally, we assess whether combining payments for carbon emission offsets with those from the water quality trading program enhances participation and performance in the emissions trading program.

Table 3.4 summarizes the payment types and levels of these programs. Annual payments from the water quality trading program, which compensates for site-specific reductions in nutrient runoff, are much higher than the CREP payments based on parcel-specific soil rental rates. Carbon payments, however, are very low given the current market rates for carbon offsets. Unlike

emissions trading programs, CREP provides a one-time upfront payment to cover initial installation costs of riparian forest buffers, which may significantly boost landowner participation.

Table 3.4 Summary Statistics of Program Attributes in Baseline Policy Simulation

Program Attribute	**Program**	**Parameter**	**Mean**	**SD**	**Description**
One-time upfront payment ($/acre)	CREP	$s_i^{CREP} = 0$ $\eta^{CREP} = 1$	2,185.60	0	Average cost of establishing riparian forest buffers (Price and Wainger, 2021)
	WQT	$s_i^{WQT} = 0$ $\eta^{WQT} = 1$	0	0	No upfront payment in the emissions trading programs
	Carbon	$s_i^{Carbon} = 0$ $\eta^{Carbon} = 1$	0	0	
Annual payment ($/acre/year)	CREP	r_i^{CREP}	231.05	91.42	Three times the parcel's annual soil rental rate
	WQT	r_i^{WQT}	487.19	182.68	Annualized cost of upgrading wastewater treatment plants to reduce N and P loads
	Carbon	r_i^{Carbon}	14.34	4.29	Average carbon offset price in 2021 auctions in the Regional Greenhouse Gas Initiative

Note: For all programs, we consider a 15-year contract that establishes and maintains riparian forest buffers with no delays in upfront payment.

We also observe significant variability in annual payments from both CREP and trading programs, but the sources of payment variability differ fundamentally. For CREP, the variability arises from the spatial heterogeneity in the opportunity cost of land use, whereas for emissions trading programs, it stems from the spatial heterogeneity in environmental benefits.

Scenario A in Table 3.5 compares the performance of the federal agricultural conservation program and two emissions trading programs as independent incentives for landowners to adopt conservation practices. The water quality trading program provides sufficient financial incentives for afforestation on agricultural land but achieves about half the participation rate and

Table 3.5 Policy Simulation Results

Program	Participation Rate	Total Benefits ($ in 1,000s)	Total Cost ($ in 1,000s)	Net benefits ($ in 1,000s)
Scenario A. Programs in isolation				
CREP	11.63%	1,993.30	735.24	1,258.06
	[5.4%, 15.6%]	[934.73, 2663.74]	[351.17, 980.60]	[582.82, 1683.23]
WQT	5.68%	1,086.20	489.65	596.55
	[2.4%, 9.3%]	[464.41, 1774.12]	[209.00, 800.22]	[255.41, 973.90]
Carbon Trading	0.15%	25.82	0.37	25.45
	[0.1%, 0.2%]	[11.77, 41.22]	[0.17, 0.59]	[11.60, 40.63]
Scenario B. Programs in competition: CREP vs Water Quality Trading				
CREP	11.43%	1,935.53	723.47	1,212.05
	[2.0%, 15.5%]	[265.68, 2654.80]	[141.51, 977.11]	[121.59, 1679.97]
WQT	0.20%	58.36	28.39	29.96
	[0.0%, 6.8%]	[0.00, 1386.60]	[0.00, 639.53]	[0.00, 748.93]
Total	11.63%	1,993.89	751.87	1,242.02
	[7.1%, 15.6%]	[1250.40, 2666.39]	[526.07, 1012.03]	[700.30, 1679.97]
Scenario C. Programs in competition: CREP vs Water Quality Trading + Carbon Trading				
CREP	11.39%	1,925.16	721.33	1,203.82
	[1.8%, 15.5%]	[219.01, 2654.80]	[127.32, 975.54]	[88.59, 1679.97]
WQT + Carbon	0.24%	69.78	34.44	35.33
	[0.0%, 7.2%]	[0.00, 1470.45]	[0.00, 686.22]	[0.00, 780.89]
Total	11.64%	1,994.94	755.78	1,239.16
	[7.2%, 15.6%]	[1271.35, 2666.39]	[527.56, 1022.43]	[702.79, 1679.97]

Note: This table presents the results of policy simulations under three distinct scenarios. Scenario A evaluates the performance of the Conservation Reserve Enhancement Program (CREP), the water quality trading (WQT) program, and the carbon trading program, each as the sole source of payment for landowners to adopt conservation practices. Scenario B allows landowners to choose payments from either the WQT program or CREP, but not both simultaneously. Scenario C examines the impact of combining payments for both carbon sequestration benefits and water quality improvements within the trading program. The parametric bootstrap with 1000 iterations (Krinsky and Robb, 1986) is used to construct the 95 percent confidence intervals of the policy simulation results, as shown in parentheses.

environmental benefits net of program costs in CREP. As shown in the stated preference study, farmland owners exhibit a high rate of time preference, valuing upfront payments significantly

more than recurring annual payments. This is evident from the estimated coefficients indicating a high marginal rate of substitution between upfront and annual payments. As a result, CREP achieves a higher participation rate than the water quality trading program, even though CREP's annual payment based on foregone crop income is on average lower than the water quality trading program's annual payment based on reduced nutrient runoff (Table 3.4). As expected from the low financial incentives of the carbon trading program (Table 3.4), few landowners establish riparian forest buffers for carbon offset credits at current market rates.

Scenario B in Table 3.5 explores a policy scenario where landowners can receive payments for riparian buffers from either emissions trading programs or CREP but cannot enroll in both simultaneously. CREP remains robust, with participation only slightly dropping from 11.6% to 11.4%, while water quality trading participation plummets from 5.7% to 0.2% when competing with CREP. Despite higher annual payments from the water quality trading program, CREP's upfront payment increases landowner enrollment in a cost-effective way. The stated preference study (Table 3.3) indicates landowners prefer upfront payments over recurring annual payments when establishing long-term conservation measures. In addition, when the two programs with different payment structure compete for the same conservation practice, landowners adversely select for the program with higher payments. As a result, the environmental benefits net of program payments of both CREP and the water quality trading program decrease by 3.7% and 95.0%, respectively, under Scenario B compared to Scenario A. Overall, we observe that when the federal conservation subsidy and the water quality trading program are in competition, the federal conservation subsidy dominates the trading incentives.

Next, we assess whether the carbon payment for agricultural conservation practices would enhance the attractiveness of the emissions trading program. Scenario C in Table 3.5 presents a

policy scenario where the emissions trading program provides payments for the carbon sequestration benefits of riparian forest buffers in addition to the payments from the water quality trading program. In this scenario, we find that adding payments for carbon offsets to the water quality trading program has little to no effect on the attractiveness or effectiveness of the emissions trading program compared to CREP. This is primarily due to the relatively low current market rate for carbon emission offsets. In addition, emissions trading programs do not offer immediate financial support for the initial costs of establishing the buffers. In contrast, CREP provides a one-time upfront payment that helps cover these initial costs, making it much more attractive to landowners.

Overall, despite the significant uncertainty in the policy simulation outcomes, we find that generous pay-for-effort incentives, where landowners receive immediate compensation for establishing forest buffers in addition to recurring annual payments, largely crowd out participation in emissions trading programs that offer only recurring annual payments. Even though emissions trading programs have the potential to provide greater environmental benefits net of payments, their effectiveness is limited by the presence and generosity of longstanding federal agricultural conservation subsidy programs. The results suggest that in agricultural afforestation activities requiring substantial upfront investment, pay-for-performance incentives (e.g., emissions trading programs) are unlikely to outcompete pay-for-effort incentives (e.g., CREP) at current market rates for emissions offsets.

3.5 Conclusion

This study provides a comprehensive analysis of the interaction between emissions trading programs and federal agricultural conservation programs in promoting afforestation activities on

agricultural land. Our findings reveal that, when evaluated in isolation, water quality trading programs have the potential to offer substantial financial incentives and greater environmental benefits net of program payments compared to traditional conservation subsidy programs. However, their effectiveness and participation rates are significantly diminished when they compete with generous federal conservation subsidies. Moreover, supplementing water quality payments with carbon payments does not enhance the attractiveness of emissions trading programs for afforestation activities, primarily because the current market rates for carbon offsets are too low.

Despite growing interest in providing carbon offset credits through agricultural conservation practices (González-Ramírez et al., 2012; Thompson et al., 2022; van Kooten and Zanello, 2023; Raina et al., 2024), agriculture accounted for less than three percent of carbon credits issued between 2013 and 2022 (USDA, 2023). Several barriers prevent farmers from participating in the carbon markets, including risk and uncertainty in carbon prices, policy uncertainty related to climate change mitigation policies, and the complexity of the market (Dumbrell et al., 2016; Kragt et al., 2017; USDA, 2023). In particular, transaction costs associated with adopting conservation practices in return for payment have been extensively examined to promote the adoption of agricultural conservation practices (Peterson et al., 2014; Palm-Forster et al., 2016; Banerjee et al., 2017; Johnston et al., 2023). However, our results suggest that even if these impediments are removed, competition with existing pay-for-effort programs would remain a significant barrier to emissions trading.

The attractiveness of emissions trading programs in our simulation is likely an upper-bound estimate, given that our analysis assumes highly favorable conditions for trading markets: frictionless trading in thick markets, the absence of restrictive rules governing trades, and no other

transaction costs. One caveat is that the relative attractiveness of trading and conservation subsidy programs may vary for different conservation programs and practices (Fleming et al., 2020).

Overall, emissions trading programs hold potential for achieving greater environmental benefits net of costs, but their success is contingent on the relative generosity of longstanding federal agricultural conservation subsidies. Future policy efforts should consider these interactions to optimize the design and implementation of financial incentives for agricultural conservation practices, ensuring that both emissions trading and federal subsidies can work together to maximize environmental benefits.

Appendix A: Appendices to Chapter 1

A1. Supplementary Tables and Figures

Table A1. Descriptive Statistics by CREP Availability: Main Analysis

Variables	Group	Mean	SD	Min	Max
Crop Loss Experience (county-by-year)					
Indemnity payouts per flooded crop acre ($/acre in 2022$)	Treated	75	113	0	953
	Untreated	88	127	0	1,112
Indemnity payout ($1,000s in 2022$)	Treated	72	347	0	9,604
	Untreated	161	1,045	0	41,600
Acres flooded (cropland)	Treated	348	1,173	0	21,031
	Untreated	614	2,469	0	67,382
Federal Crop Insurance Program Participation (county-by-year)					
Acres insured (1,000s)	Treated	165	100	4	585
	Untreated	137	95	0	531
Coverage level insured (%, area-weighted)	Treated	71	8	47	86
	Untreated	69	8	0	85
Conservation Reserve Enhance Program (CREP) (post-policy period, county-by-year)					
Number of acres enrolled	Treated	727	1,857	0	20,197
Annual program payments ($1,000s in 2022$)	Treated	117	323	0	4,819
Weather (county-by-year)					
Total Precipitation (mm)					
Post-harvest, Oct.-Mar. 1988-1997	Treated	356	158	140	871
	Untreated	449	230	146	896
Growing season, Apr.-Sept. 1989-1997	Treated	632	74	433	931
	Untreated	662	83	482	944
Growing degree days (10-29 Celsius)					
Post-harvest, Oct.-Mar. 1988-1997	Treated	194	161	53	1,068
	Untreated	278	208	71	1,064
Growing season, Apr.-Sept. 1989-1997	Treated	1,627	269	1,206	2,692
	Untreated	1,799	331	1,261	2,663
Num. Obs. (county-by-year): Treated 8,500 (250-by-34); Untreated 5,100 (150-by-34)					

Note: The table presents summary statistics of variables used in the main analysis for 400 counties during 1989-2022. Treated group refers to counties that introduced CREP between 1998 and 2011 and untreated group refers to counties that have not introduced CREP during the analysis period.

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

Table A2. Timing Variation of Conservation Reserve Enhancement Program (CREP) Availability and Participation

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

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

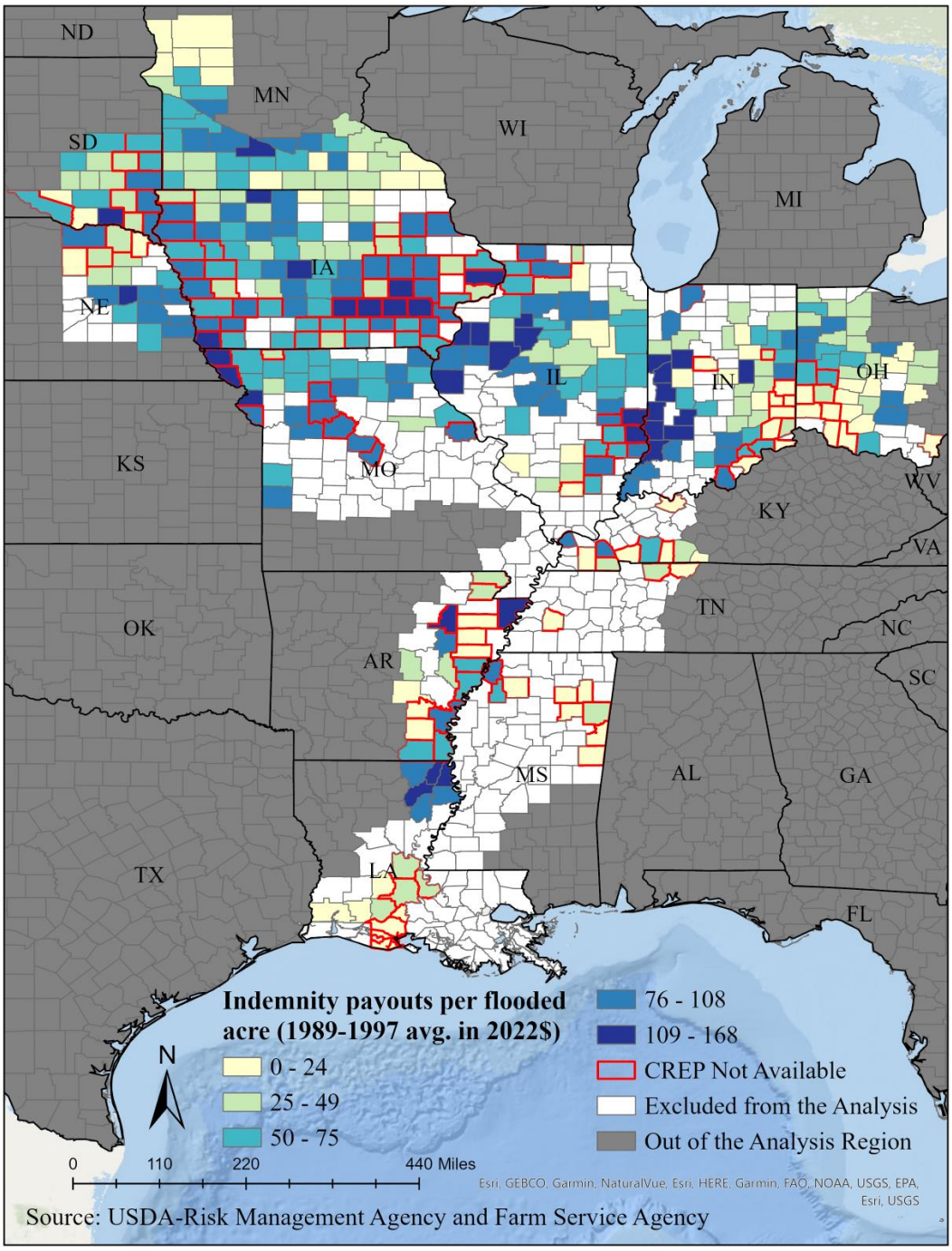
Source: USDA Farm Service Agency

Table A3. Estimated Impact of CREP Introduction on Flood Damage on Cropland

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

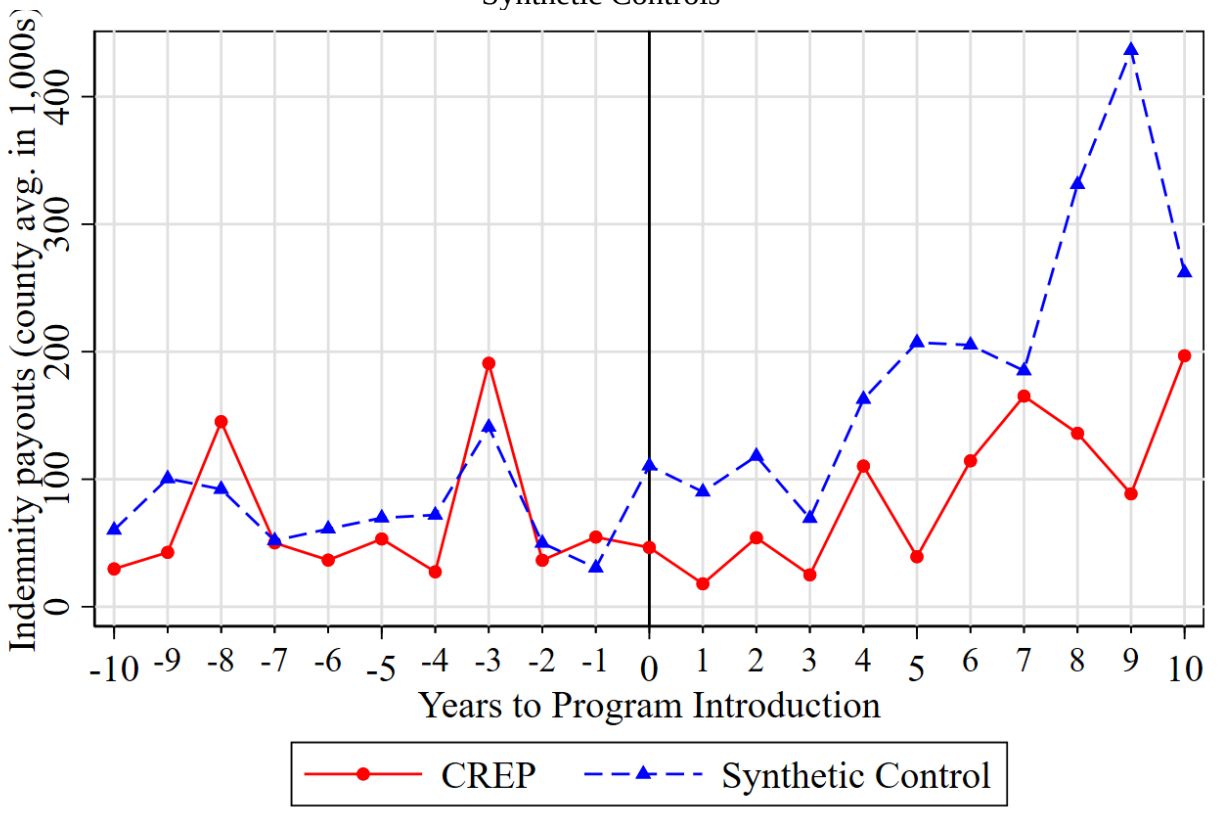
Note: The table presents the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss, measured by total indemnity payouts (2022$) per flooded crop acre, by event time (the number of years to the program introduction). Two DID estimators are implemented: (i)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

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



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

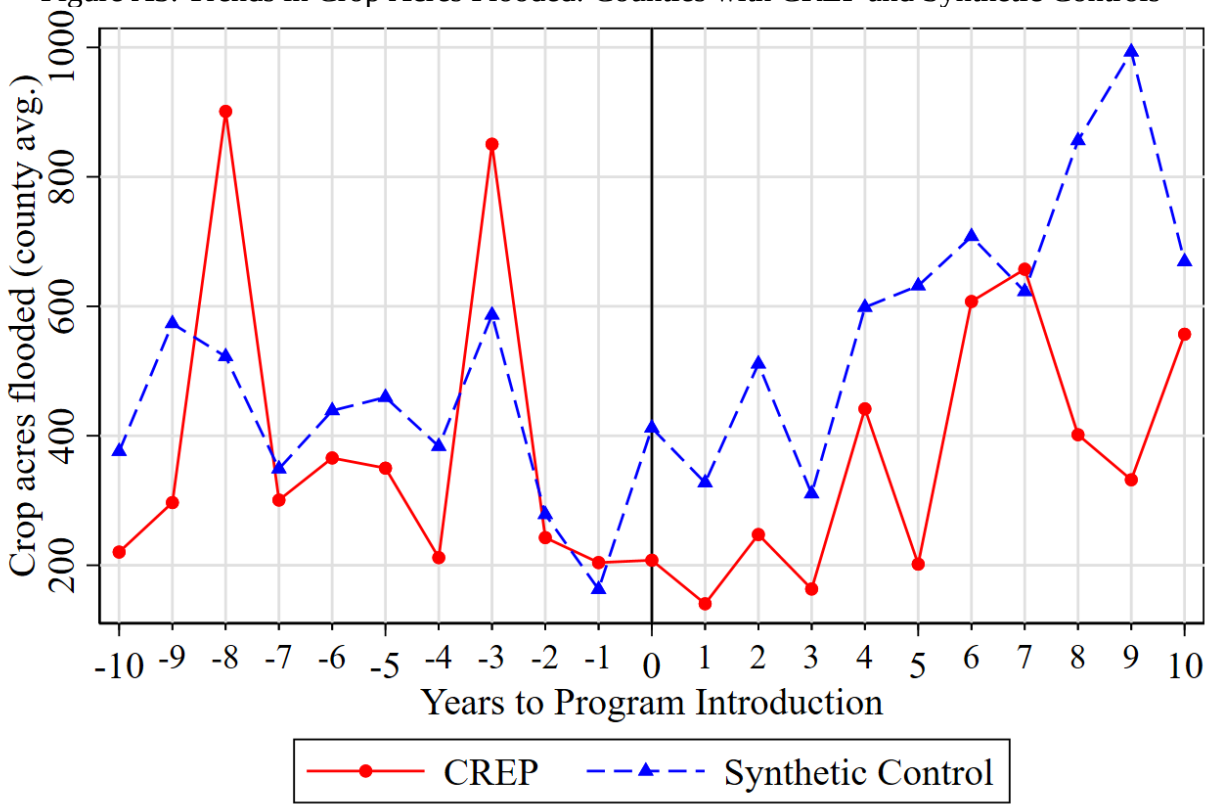
Figure A2. Trends in Indemnity Payouts due to Flooded Crop Loss: Counties with CREP and Synthetic Controls



Pre-outcome Avg.: CREP 67344, Synthetic Control 72890, Pre-Diff. = -5546
Post-outcome Avg.: CREP 90406, Synthetic Control 197993, Post-Diff = -107587

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

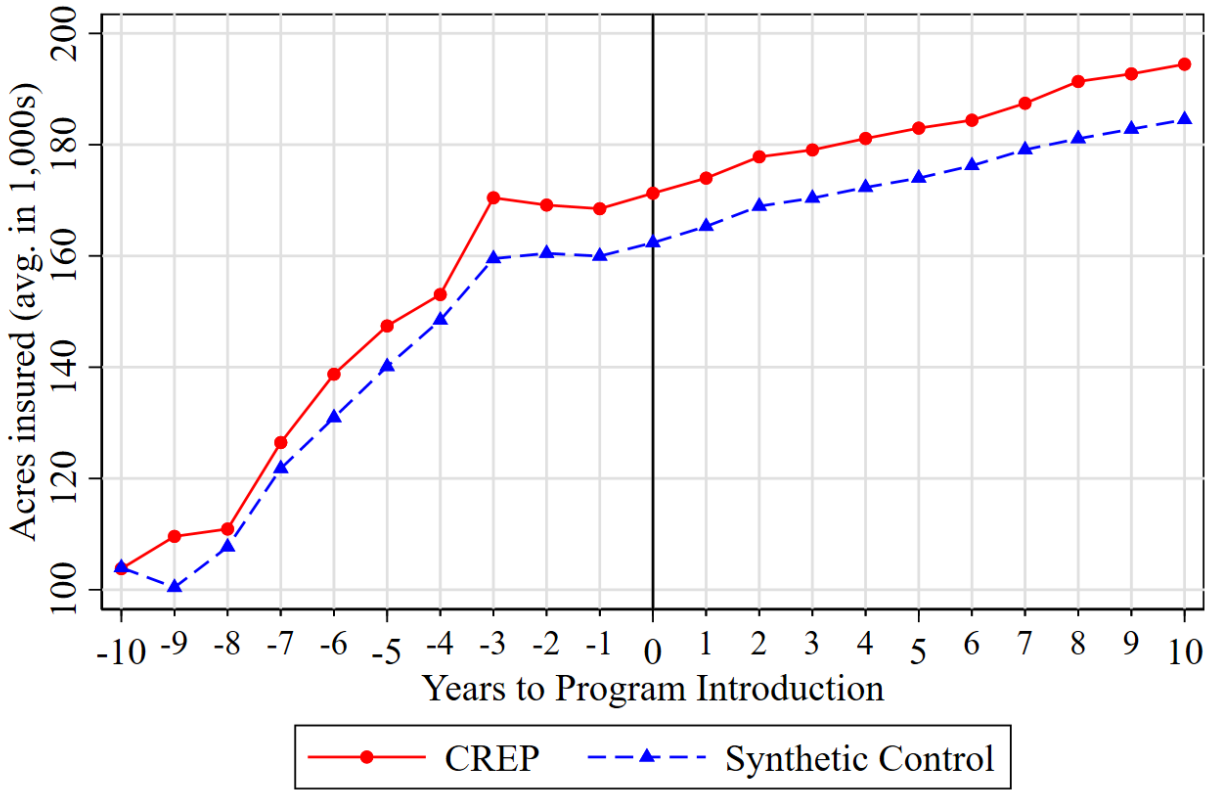
Figure A3. Trends in Crop Acres Flooded: Counties with CREP and Synthetic Controls



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

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

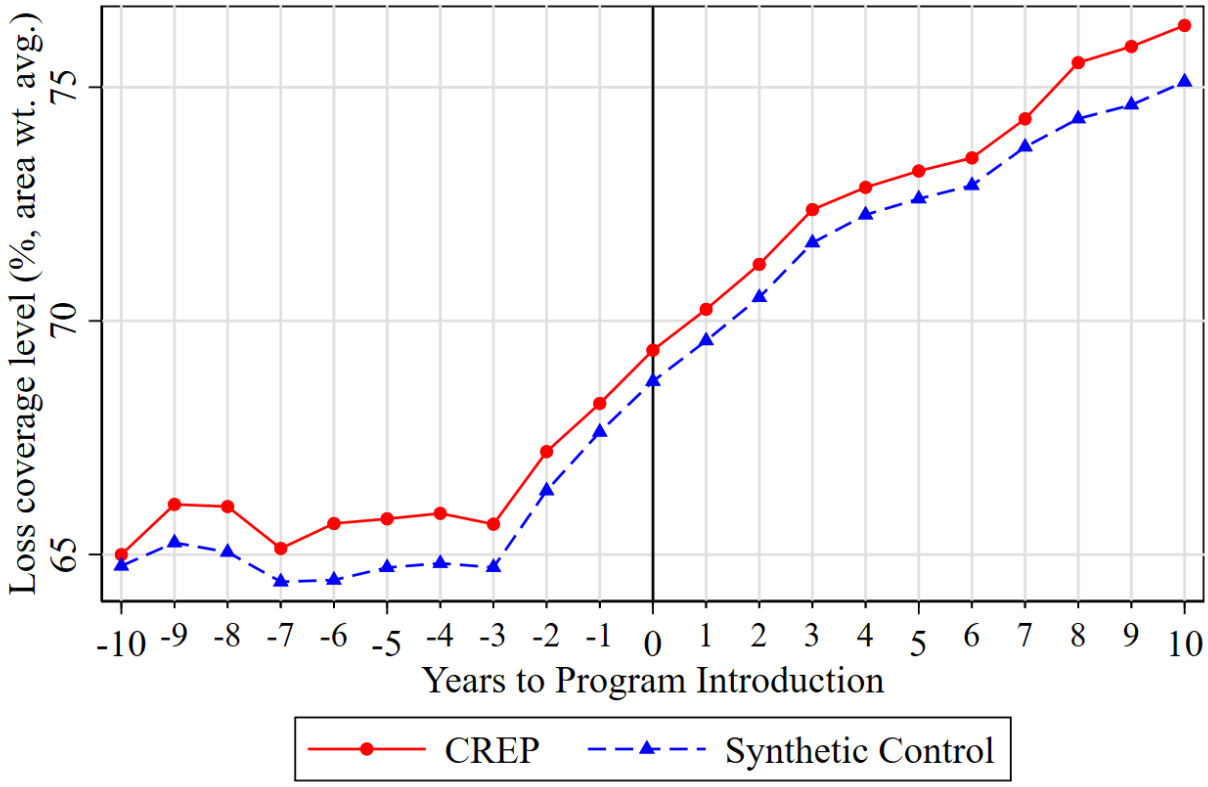
Figure A4. Trends in Acres Insured under the Federal Crop Insurance Program: Counties with CREP and Synthetic Controls



Pre-outcome Avg.: CREP 140.5, Synthetic Control 133.2, Pre-Diff. = 7.3
Post-outcome Avg.: CREP 183.3, Synthetic Control 174.3, Post-Diff. = 9

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

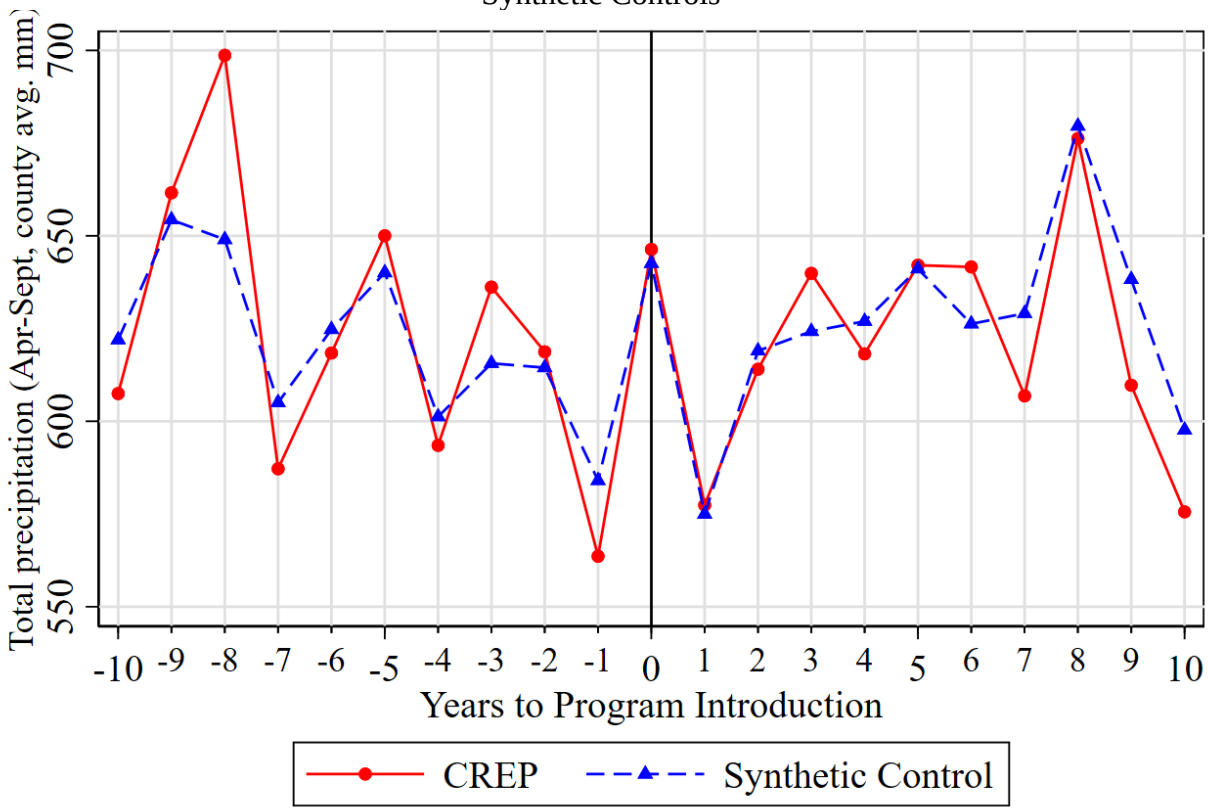
Figure A5. Trends in Insurance Coverage Level under the Federal Crop Insurance Program: Counties with CREP and Synthetic Controls



Pre-outcome Avg.: CREP 66.1, Synthetic Control 65.2, Pre-Diff. = .9
Post-outcome Avg.: CREP 73.2, Synthetic Control 72.4, Post-Diff. = .8

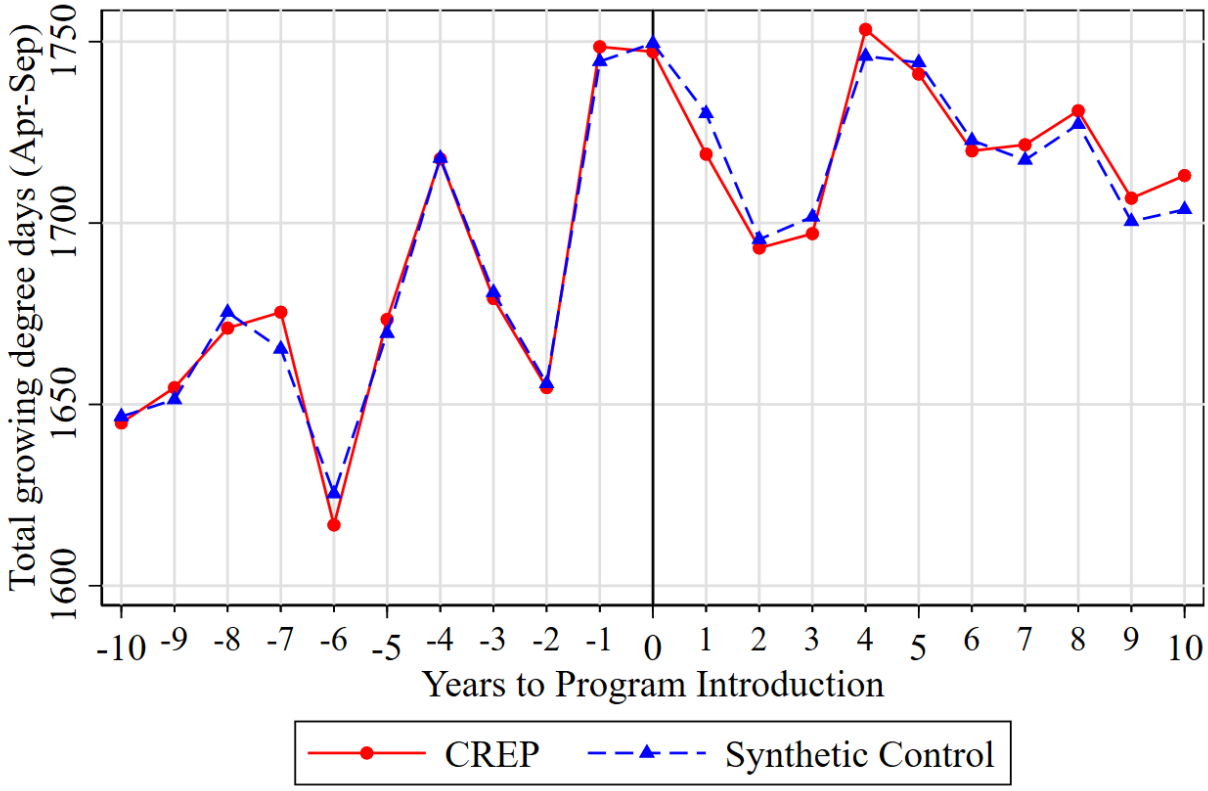
Note: The graph shows how the coverage level for acres insured under the federal crop insurance program has changed by event time (x-axis) for both 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of 150 counties without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

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



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

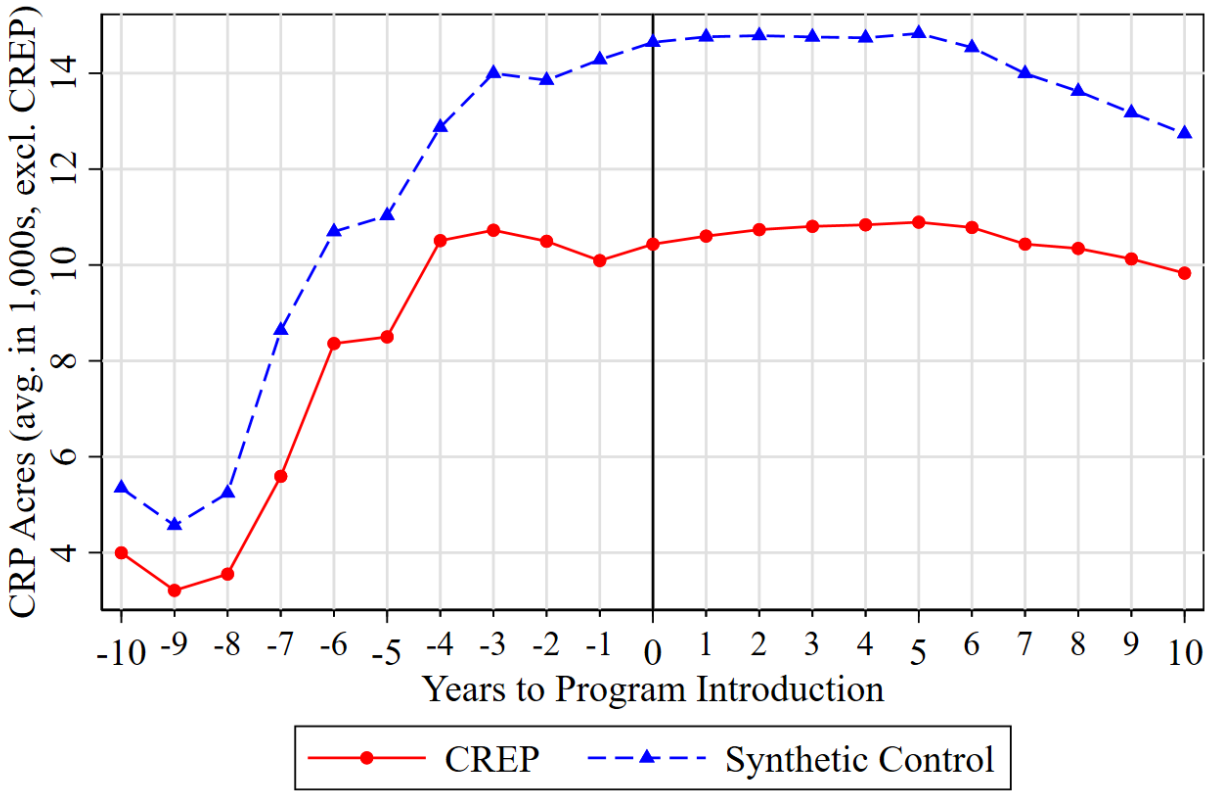
Figure A7. Trends in Growing Degree Days (10-29 Celsius) during Crop Growing Season: Counties with CREP and Synthetic Controls



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

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

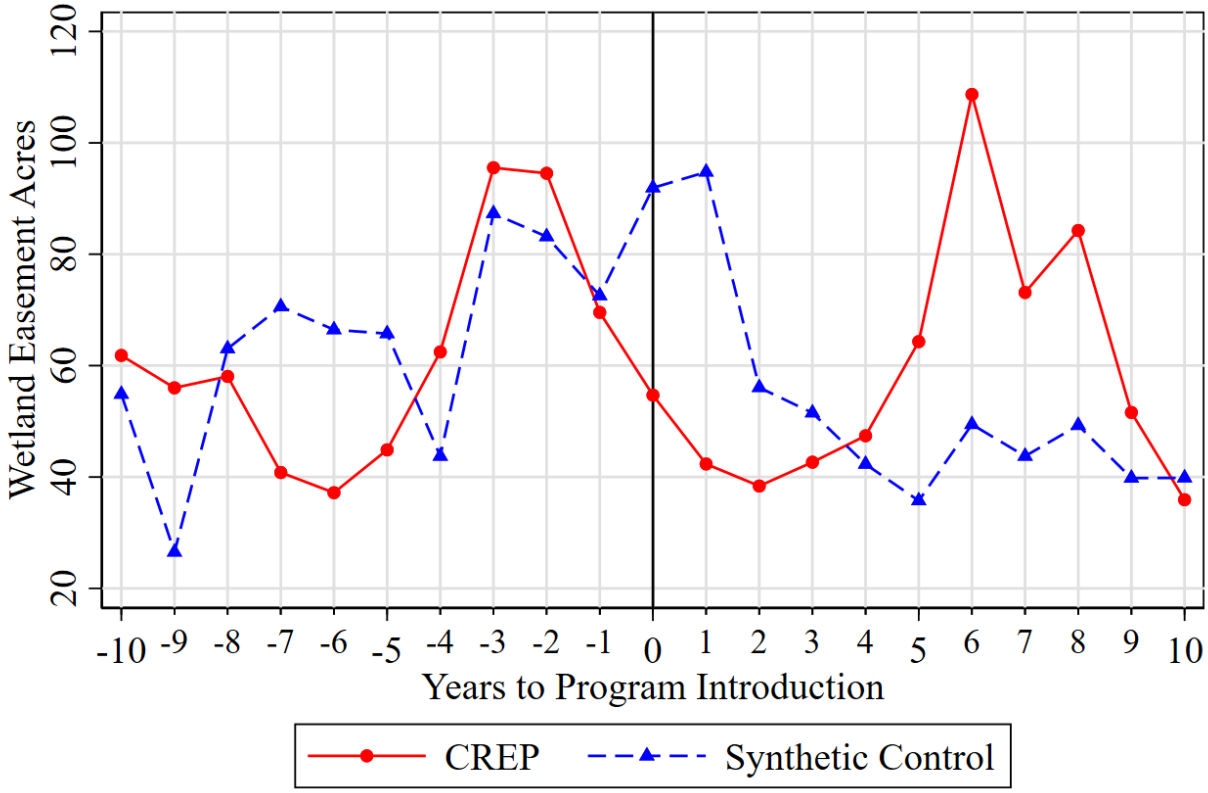
Figure A8. Trends in Acreage enrolled under the Conservation Reserve Program (excluding CREP) : Counties with CREP and Synthetic Controls



Pre-outcome Avg.: CREP 7.5, Synthetic Control 10, Pre-Diff. = -2.5
Post-outcome Avg.: CREP 10.5, Synthetic Control 14.2, Post-Diff. = -3.7

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

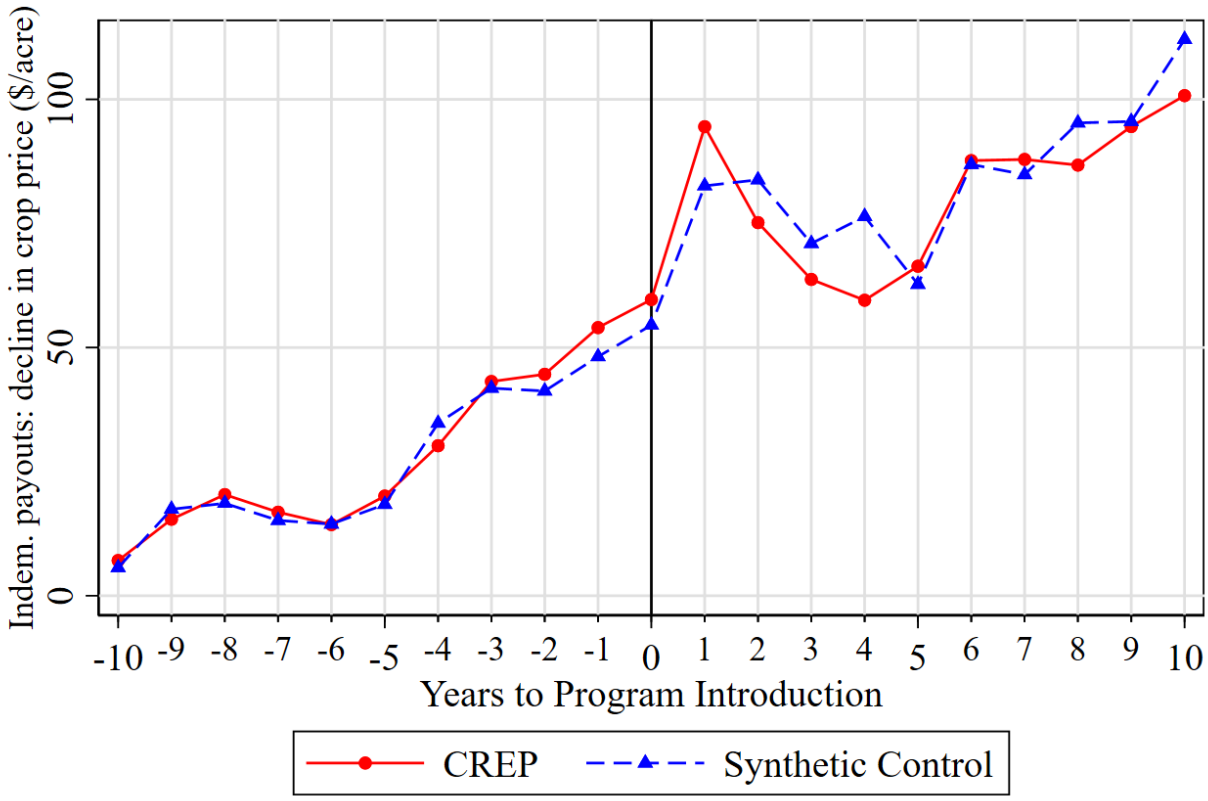
Figure A9. Trends in Acreage enrolled under the Agricultural Conservation Easement Program's Wetland Reserve Easement: Counties with CREP and Synthetic Controls



Pre-outcome Avg.: CREP 61.4, Synthetic Control 62.9, Pre-Diff. = -1.5
Post-outcome Avg.: CREP 58.5, Synthetic Control 54, Post-Diff. = 4.5

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

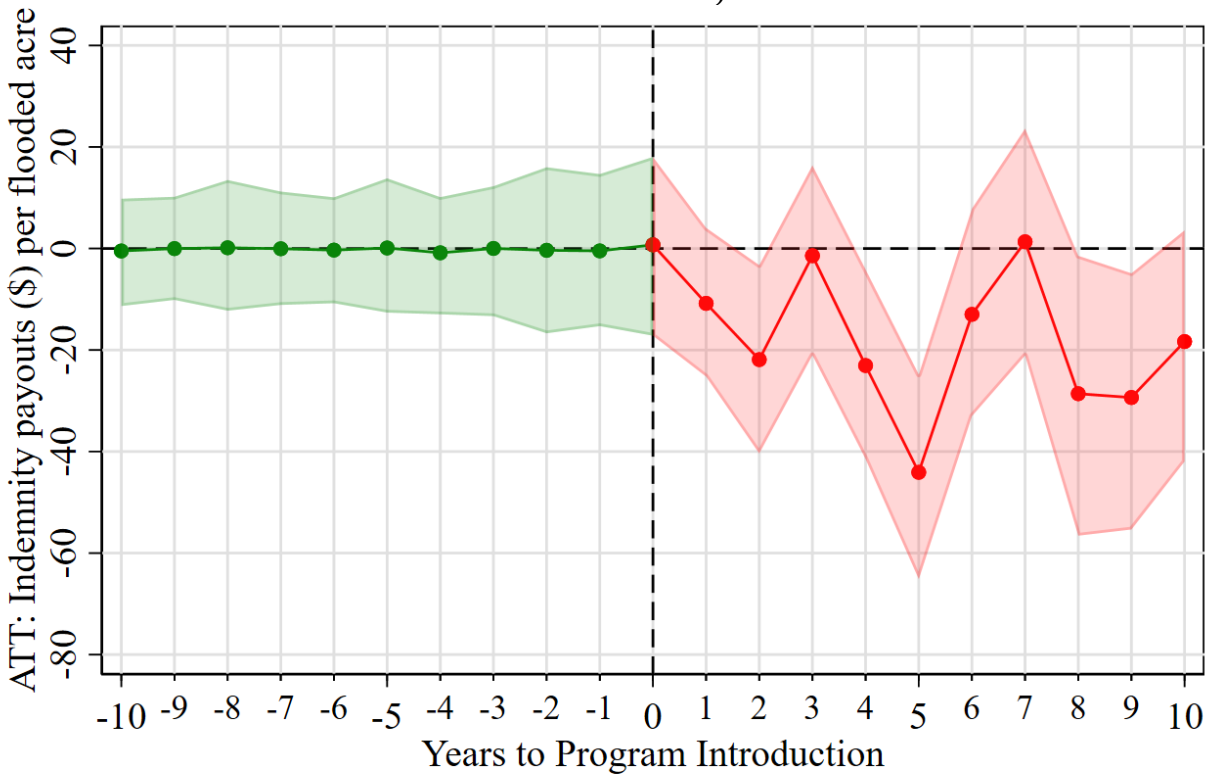
Figure A10. Trends in Indemnity Payouts due to Decline in Crop Price: Counties with CREP and Synthetic Controls



Pre-outcome Avg.: CREP 26.5, Synthetic Control 25.5, Pre-Diff. = 1
Post-outcome Avg.: CREP 79.7, Synthetic Control 82.3, Post-Diff. = -2.6

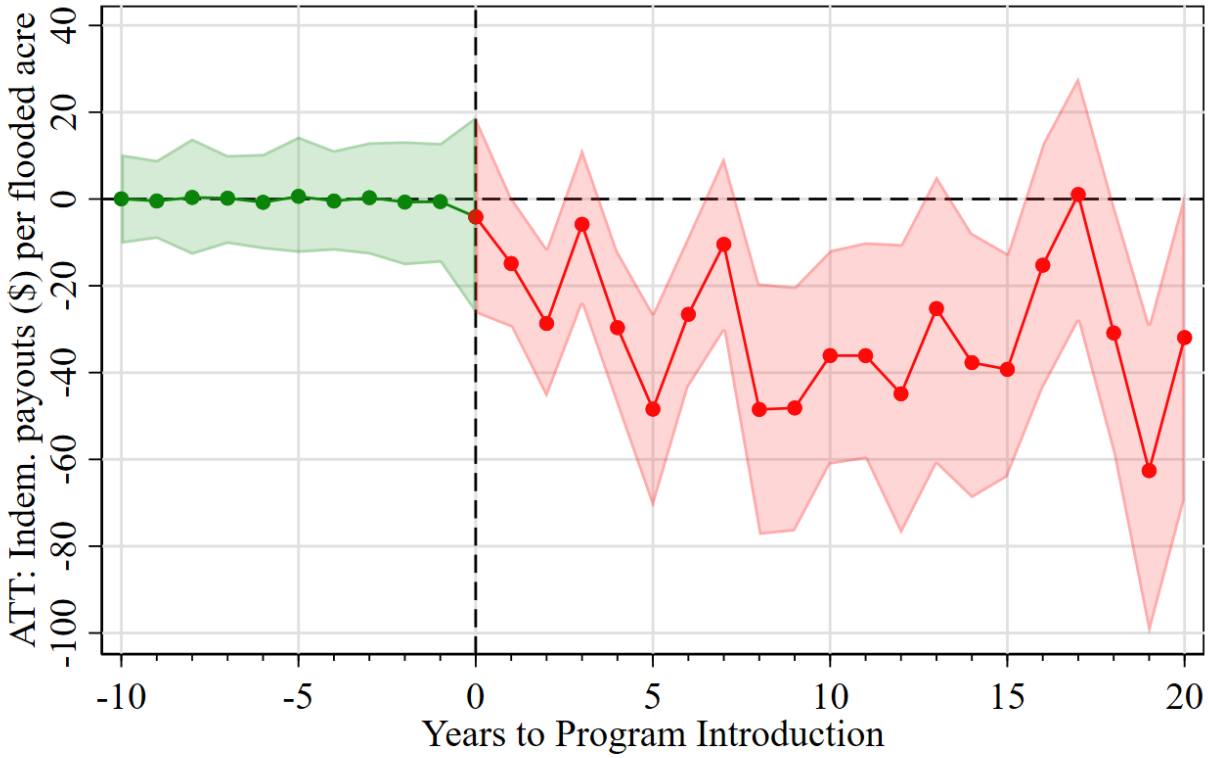
Note: The graph shows trends in county-level average indemnity payouts due to decline in crop price for acres insured under the federal crop insurance program (y-axis) across event time (x-axis) for both 250 counties with Conservation Reserve Enhancement Program (CREP) and their synthetic controls constructed based on a weighted average of 150 counties without CREP.

Figure A11. Estimated Impact of CREP Introduction on Flooded Crop Loss (ATT without weather covariates)



Note: The graph shows the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss (indemnity payouts per flooded crop acre, y-axis) across event time (x-axis) with 95 percent confidence intervals. The estimated average program effect is calculated by comparing the average change in crop loss relative to pre-policy average between 250 counties with CREP and their synthetic controls constructed based on a weighted average of 150 counties without CREP. Only lagged outcomes are used in choosing weights of untreated and not-yet treated counties to construct synthetic controls. Confidence intervals (95%) are constructed using wild bootstrap.

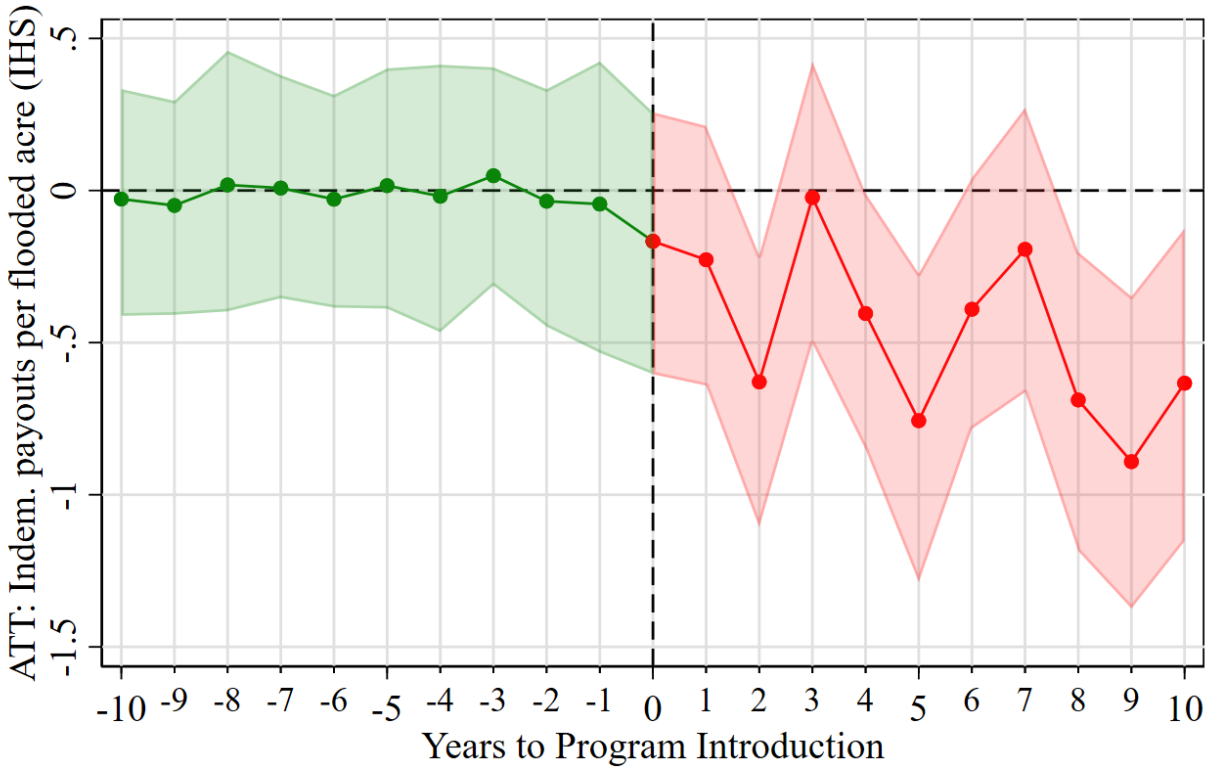
Figure A12. Estimated Impact of CREP Introduction on Flooded Crop Loss (ATT: up to 21 event times)



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

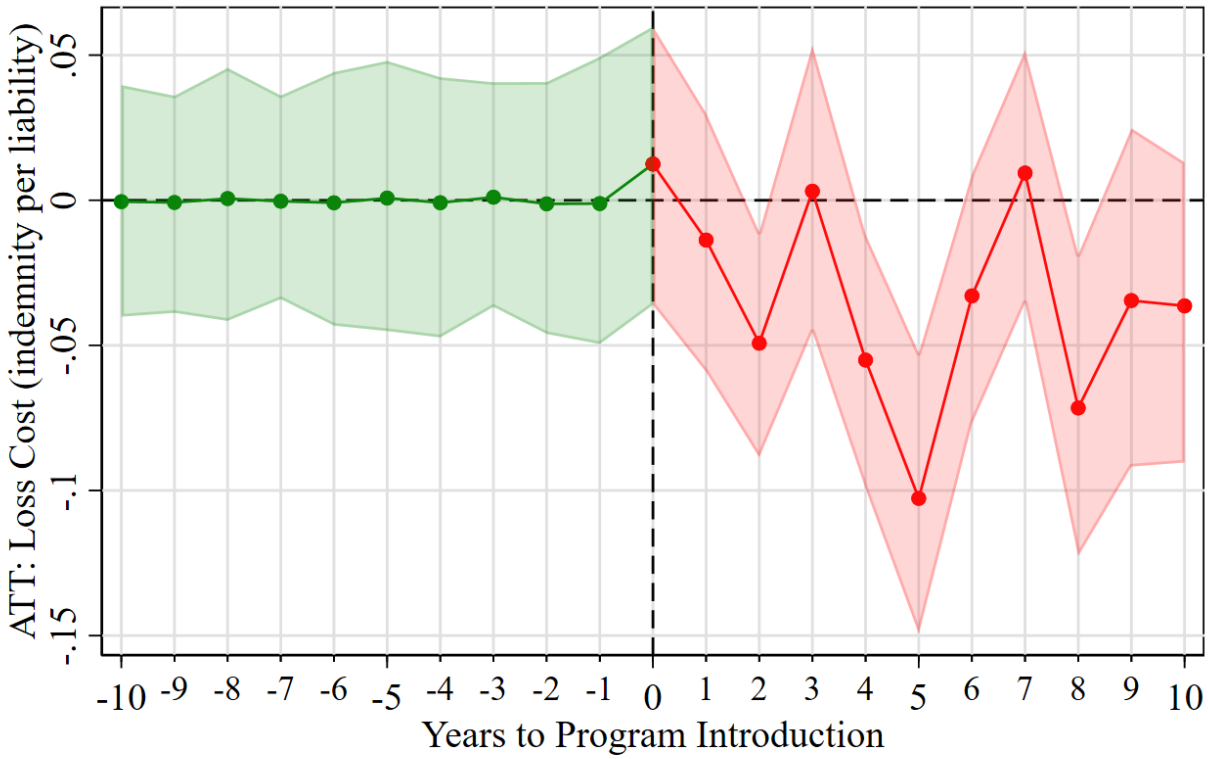
Note: The graph shows the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss, measured by indemnity payouts per flooded acre (y-axis), across event time (x-axis) with 95 percent confidence intervals. The estimated average program effect is calculated by comparing the average change in crop loss relative to pre-policy average between 250 counties with CREP and their synthetic controls constructed based on a weighted average of 150 counties without CREP. In addition to lagged outcomes, precipitation (mm) and growing degree days during the post-harvest (October to March) and crop growing seasons (April to September) are used as auxiliary covariates in choosing weights of untreated and not-yet treated counties to construct synthetic controls. Confidence intervals (95%) are constructed using wild bootstrap.

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



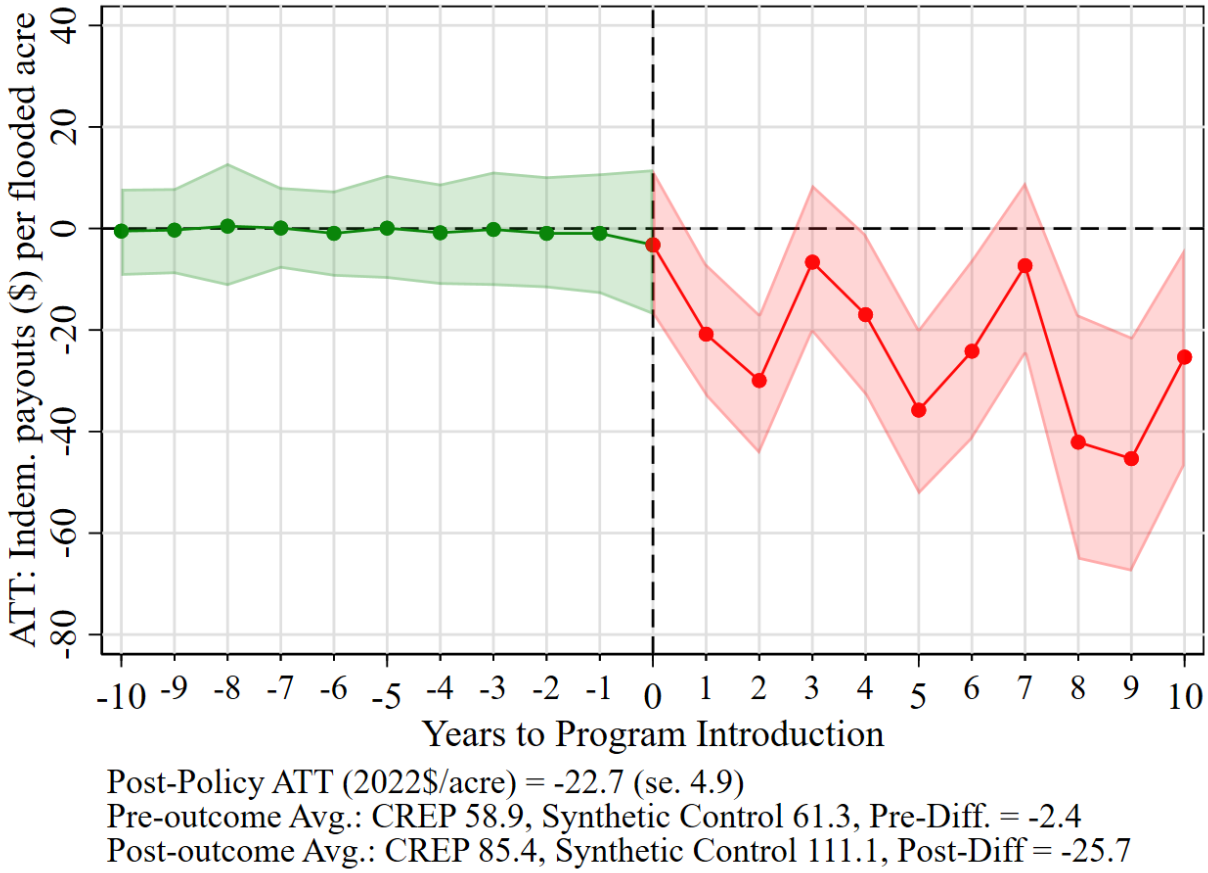
Note: The graph shows the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss, measured by inverse hyperbolic sine (IHS) transformation of indemnity payouts per flooded acre (y-axis), across event time (x-axis) with 95 percent confidence intervals. The estimated average program effect is calculated by comparing the average change in crop loss relative to pre-policy average between 250 counties with CREP and their synthetic controls constructed based on a weighted average of 150 counties without CREP. In addition to lagged outcomes, precipitation (mm) and growing degree days during the post-harvest (October to March) and crop growing seasons (April to September) are used as auxiliary covariates in choosing weights of untreated and not-yet treated counties to construct synthetic controls. Confidence intervals (95%) are constructed using wild bootstrap.

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



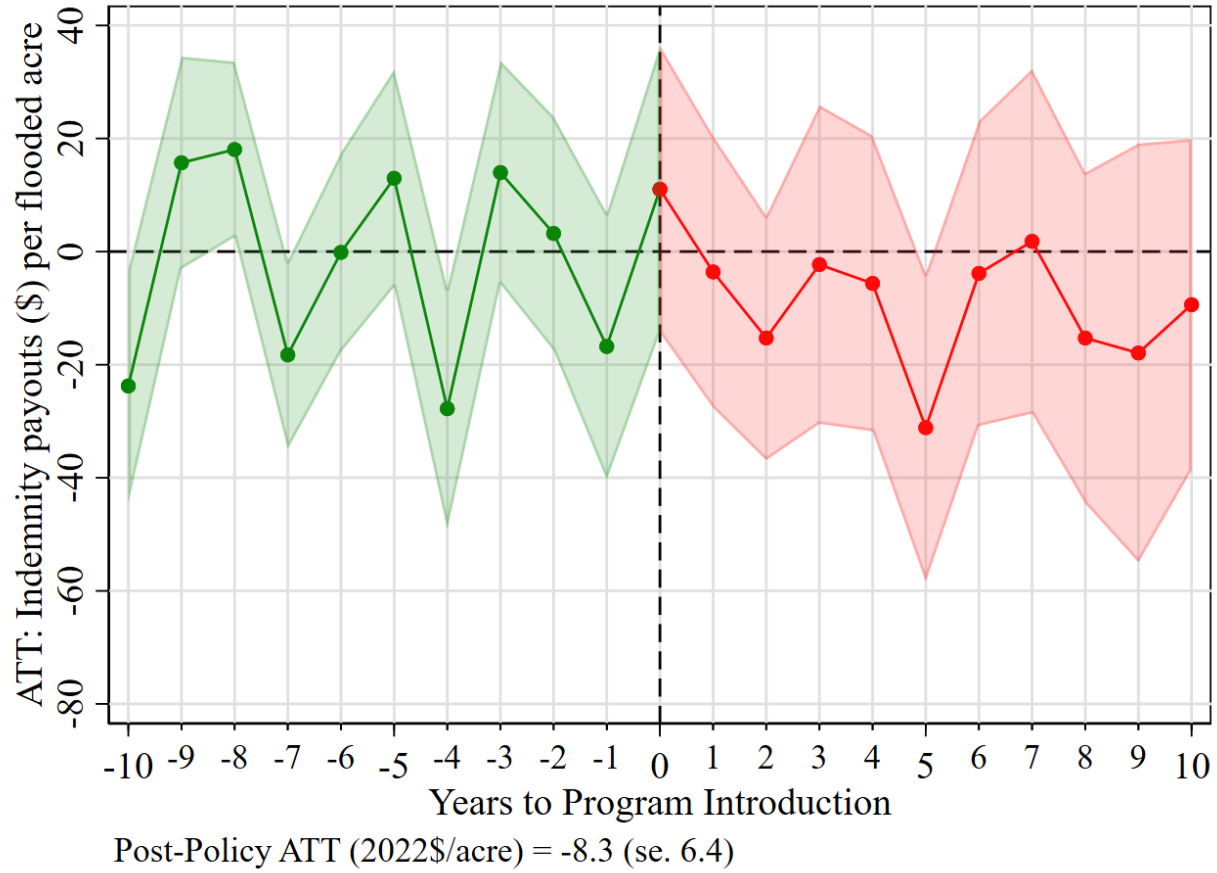
Note: The graph shows the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss, measured by loss cost (indemnity payouts per liability, y-axis), across event time (x-axis) with 95 percent confidence intervals. The estimated average program effect is calculated by comparing the average change in crop loss relative to pre-policy average between 250 counties with CREP and their synthetic controls constructed based on a weighted average of 150 counties without CREP. In addition to lagged outcomes, precipitation (mm) and growing degree days during the post-harvest (October to March) and crop growing seasons (April to September) are used as auxiliary covariates in choosing weights of untreated and not-yet treated counties to construct synthetic controls.

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



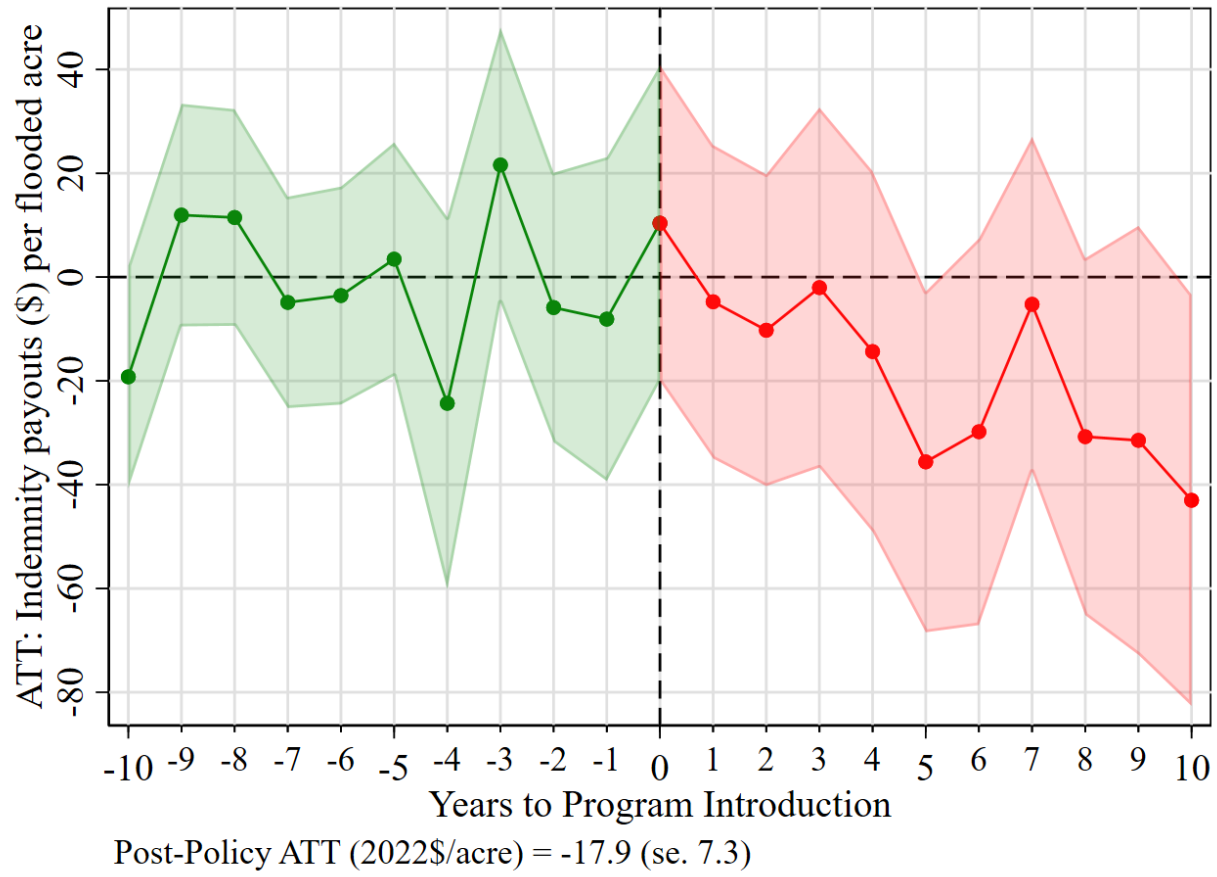
Note: The graph shows the estimated impact of Conservation Reserve Enhancement Program (CREP) introduction on flooded crop loss, measured by indemnity payouts per flooded acre (y-axis), across event time (x-axis) with 95 percent confidence intervals. The estimated average program effect is calculated by comparing the average change in crop loss relative to pre-policy average between 363 counties with CREP and their synthetic controls constructed based on a weighted average of 272 counties without CREP. In addition to lagged outcomes, precipitation (mm) and growing degree days during the post-harvest (October to March) and crop growing seasons (April to September) are used as auxiliary covariates in choosing weights of untreated and not-yet treated counties to construct synthetic controls.

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



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

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



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

A2. Synthetic Control Method: Supplementary Materials

The empirical methodology employed to estimate the causal impact of CREP introduction on flooded crop loss utilizes a partially pooled synthetic control method with an intercept shift. This approach estimates the counterfactual trajectory of an average crop loss in the treated group by allocating weights across untreated counties to maximize the similarity between the synthetic control counties and the treated counties. The method considers two imbalance measures to achieve this objective: (i) the average difference in pre-policy outcome between the treated and synthetic control counties (individual fit), and (ii) the difference in average pre-policy outcome between the treated and synthetic control counties (pooled fit) (Doudchenko & Imbens, 2016; Ferman & Pinto, 2021; Ben-Michael et al., 2022).

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

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

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

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

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

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

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

where the relative importance of the average outcome fit (pooled fit) to individual outcome fit increases with parameter $\nu \in [0,1]$.[22] To ensure unique weights and avoid interpolation biases, a regularization penalty term λ is added (Abadie et al., 2015; Doudchenko & Imbens, 2016; Abadie & L'Hour, 2021; Arkhangelsky et al., 2021).[23] As a baseline, I follow Ben-Michael et al (2022) and set ν to be the ratio of the pooled fit to the average unit-level fit as a baseline:

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

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

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

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

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

where the intercept shift represents the average pre-policy outcome difference between treated county j and its synthetic control county. By combining equations (A.5) with (1.7), I obtain the form of the weighted DID estimator $\hat{\tau}_{jk}$:

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

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

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

Appendix B: Appendices to Chapter 2

B1. Derivation of the Optimal Multi-Period Contract

The agent's participation condition in a payment for ecosystem services (PES) contract spanning T periods is:

$$(1-s)k_n + \left(\prod_{t=1}^{T-1} F_{nt}\right)\left(\sum_{t=0}^{T-1} \delta^t r_n\right) \tag{B.1}$$

$$+\sum_{j=0}^{T-2}\left\{\left(\prod_{t=0}^{j} F_{nt}\right)\int_{L_{nj+1}}^{\varepsilon_{n,max}}\left[\begin{array}{c}\sum_{l=0}^{j}\delta^l r_n \\ +\left(\sum_{q=j+1}^{T-1}\delta^q v_{nq}\right)\varepsilon_{nj+1} \\ -\delta^{j+1}\left(p_{nj+1}+c_{nj+1}\right)\end{array}\right] f_n\left(\varepsilon_{nj+1}\right)d\varepsilon_{nj+1}\right\} \geq \sum_{t=0}^{T-1}\delta^t v_{nt}.$$

The left-hand side of condition (B.1) represents the time 0 expected net program return to the agent: out-of-pocket practice installation costs, a series of fixed annual payments weighted by the probability of contract completion, and the sum of expected returns from crop production when the contract is terminated at each time 1 to $T-1$ weighted by corresponding probabilities. The right-hand side of this condition represents the time 0 expected net crop return for T periods, that is, the agent's opportunity cost.

The principal's objective function is:

$$max_{r_n,p_1,p_2,\ldots,p_{T-1}} -sk_n + \left(\prod_{t=1}^{T-1} F_{nt}\right)\left(\sum_{t=0}^{T-1}\delta^t(B_{nt}-r_n)\right) \tag{B.2}$$

$$+\sum_{j=0}^{T-2}\left(\prod_{t=0}^{j} F_{nt}\right)\left(1-F_{nj+1}\right)\left[\sum_{l=0}^{j}\delta^l(B_{nl}-r_n)+\delta^{j+1}p_{nj+1}\right],$$

subject to the participation constraint, condition (B.1).

The principal chooses the minimum annual payment r_n such that the agent's participation constraint in equation (B.1) holds with equality. Thus, annual payment under the optimal contract r_n^* is the minimum amount of annual payment that ensures the agent's participation in the program under the optimal penalty structure:

$$r_n^* = \frac{\left\{\begin{array}{c} \sum_{t=0}^{T-1} \delta^t \, v_{nt} + (1-s)k_n \\ -\sum_{j=0}^{T-2}\left\{\left(\prod_{t=0}^{j} F_{nt}^*\right)\int_{L_{nj+1}^*}^{\varepsilon_{n,max}}\left[\left(\sum_{q=j+1}^{T-1}\delta^q \, v_{nq}\right)\varepsilon_{nj+1} - \delta^{j+1}c_{nj+1}\right]f_n\left(\varepsilon_{nj+1}\right)d\varepsilon_{nj+1}\right\} \\ +\sum_{j=0}^{T-2}\left\{\left(\prod_{t=0}^{j} F_{nt}^*\right)\left(1-F_{nj+1}^*\right)\sum_{q=j+1}^{T-1}\delta^q \, B_{nq}\right\} \end{array}\right\}}{\sum_{t=0}^{T-1}\delta^t} \quad (B.3)$$

where F_t^* is obtained from equation (2.16) under the optimal penalty schedule p_t^*.

Assuming that the participation constraint is binding and substituting it into the principal's objective function yields the concentrated objective function:

$$W_{nT} \equiv -k_n + \left(\prod_{t=1}^{T-1} F_{nt}\right)\left(\sum_{t=0}^{T-1}\delta^t \, B_{nt}\right) \quad (B.4)$$

$$+\sum_{j=0}^{T-2}\left\{\left(\prod_{t=0}^{j} F_{nt}\right)\int_{L_{nj+1}}^{\varepsilon_{n,max}}\left[\sum_{l=0}^{j}\delta^l \, B_{nl} + \left(\sum_{q=j+1}^{T-1}\delta^q \, v_{nq}\right)\varepsilon_{nj+1} - \delta^{j+1}c_{nj+1}\right]f_n\left(\varepsilon_{nj+1}\right)d\varepsilon_{nj+1}\right\}$$

$$-\sum_{t=0}^{T-1}\delta^t \, v_{nt}.$$

Taking the derivative of the concentrated objective function in equation (B.4) with respect to the penalty levied due to premature contract termination in each time t $(0 \le t \le T-1)$ yields a series of first-order conditions:

$$\frac{W_{nT}}{p_{nt}} \equiv \delta^t(B_{nt} - r_n - p_{nt}) + \sum_{l=t+1\le T-1}^{T-1}\left(\prod_{z=t+1\le l-1}^{l-1} F_{nz}\right)\delta^l\left[F_{nl}(B_{nl} - r_n) + (1-F_{nl})p_{nl}\right]. \quad (B.5)$$

We solve this set of first order conditions recursively. It is straightforward to show that the optimal penalty in the penultimate period in the contract, p_{nT-1} equals net environmental benefits in period T, i.e., period T environmental benefits minus the annual payment (which is invariant over time):

$$\delta^{T-1}(B_{nT} - r_n - p_{nT-1}) = 0 \Leftrightarrow p^*_{nT-1} = B_{nT} - r_n. \quad (B.6)$$

Now consider the antepenultimate period, $T-2$. The first order condition in this case, after substituting the optimal period $T-1$ penalty p_{nT-1} yields:

$$p^*_{nT-2} = B_{nT-2} - r_n + \delta(B_{nT-1} - r_n). \quad (B.7)$$

Similarly, the first order condition for period $T-3$ is, after substitution for p_{nT-1} and p_{nT-2} :

$$p^*_{nT-3} = B_{nT-3} - r_n + \delta(B_{nT-2} - r_n) + \delta^2(B_{nT-1} - r_n). \quad (B.8)$$

This sequence suggests the following optimal penalty for an arbitrary period $t < T$:

$$p^*_{nt} = \frac{1}{\delta^t}\left[\sum_{j=t}^{T-1} \delta^j \left(B_{nj} - r_n\right)\right]. \quad (B.9)$$

To prove that this penalty structure is optimal, assume that it holds for an arbitrary time period τ ($1 \leq \tau \leq T-1$), i.e., that:

$$p^*_{n\tau} = \frac{1}{\delta^\tau}\left[\sum_{j=\tau}^{T-1} \delta^j \left(B_{nj} - r_n\right)\right], \quad (B.10)$$

The first order condition for period $\tau - 1$, after substitution for $p^*_{n\tau}$, implies that:

$$p^*_{n\tau-1} = \frac{1}{\delta^{\tau-1}}\left[\sum_{j=\tau-1}^{T-1} \delta^j \left(B_{nj} - r_n\right)\right]. \quad (B.11)$$

Thus, if the formula holds for one period, it must hold for the previous one as well. We have already shown that this formula holds for periods $T-1$, $T-2$, and $T-3$, which implies that it holds for all $t < T$. QED

B2. Calculating the Environmental Benefits of Riparian Buffers

Total environmental benefits of converting cropland to grassed riparian buffer equal the sum of direct and indirect benefits for water quality improvement in this numerical policy simulation. The direct benefit of cropland within the riparian buffer zone being converted to a grass buffer comes primarily from the difference in nutrient and sediment loads between the two types of land use. Cropland has higher nutrient loads because of fertilizer applications, while the grass cover in the buffer area does not have fertilizer applied. Cropland has higher sediment loads as well because it has less dense ground coverage than grass. This direct benefit is assumed to be obtained immediately when the grass buffer is planted (i.e., fertilizer is no longer used and ground cover becomes more dense) and stays at the same level over the contract lifetime. The direct benefit is estimated by the difference in pollutant loads between grass cover and cropland multiplied by the delivery factor and per-pound social cost for each pollutant type *z*:

$$DB_n = \sum_{z=N,P,S} m^z\left(d^z_{n,crop}\alpha^z_{n,crop} - d^z_{n,grass}\alpha^z_{n,grass}\right) \qquad (B.12)$$

Three main types of agricultural nonpoint source pollutants are denoted by z: total nitrogen (N), total phosphorus (P), and total suspended solids (S). These are the three pollutants that have mandated reductions from agricultural sources under Chesapeake Bay TMDL requirements. The coefficients $\alpha^z_{n,crop}$ and $\alpha^z_{n,grass}$ are the per-acre loads of pollutant $z = \{N, P, S\}$ from cropland and grass cover for parcel n measured at the edge of the nearest stream. The parameter $d^z_{n,crop}$ and $d^z_{n,grass}$ are delivery ratio factors to account for attenuation occurring while the pollutant loads are transported from cropland and grass riparian buffer for parcel n, respectively, to the Chesapeake Bay. The parameter m^z is the per-pound social cost of pollutant load *z* in the Bay, which converts the reduced amount of pollutant load z to the Chesapeake Bay into a monetary value.

The indirect benefits of converting cropland into grass buffer are obtained as the installed riparian buffer filters nutrient and sediment runoff from neighboring cropland before they can enter the stream or waterway. The indirect benefits grow over time as the vegetative grass buffer establishes and matures over time. For each pollutant type z, the amount of pollutant load treated by an acre of installed riparian buffer is equal to the product of three parameters: (i) proportion of pollutant loads removed by an acre of t-year-old grass buffer, η_{nt}^{z} (i.e., practice efficiency rate), (ii) the ratio of neighboring cropland acres to buffer acres for which the efficiency rate applies, x^{z}, and (iii) pollutant loads from an acre of cropland, $\alpha_{n,crop}^{z}$. Then, the indirect benefits of the grass buffer at time t, IB_{nt}, are:

$$IB_{nt} = \sum_{z=N,P,S} m^{z}\, \alpha_{n,crop}^{z} x^{z} \eta_{nt}^{z} d_{n,crop}^{z}, \qquad (B.13)$$

where the parameters for delivery factor $d_{n,crop}^{z}$ and social cost m^{z} are already defined above.

The environmental benefits from installing the riparian grass buffer vary depending on the county, land-river segment (i.e., watershed), and hydrogeomorphic region where the parcel is located. We start with the parameter values used for the direct benefits in equation B.12. Estimated N, P, and S loads from cropland and grass cover at the edge-of-stream for parcel n, $\alpha_{n,crop}^{z}$and $\alpha_{n,grass}^{z}$, vary across county and are obtained from Chesapeake Assessment Scenario Tool (CAST) – Loads Report (CBP, 2019). When the program-eligible cropland in the parcel is located spanning across a county border, we obtain the acreage-weighted pollutant load. Compared to grass cover, cropland in general generates substantially more pollutant loads at the edge-of-stream. Cropland generates, on average, annual loads of 24.9 N lbs/acre, 0.9 P lbs/acre, and 1,200.1 S lbs/acre for the 7,223 parcels included in the simulation. Meanwhile, grass cover generates, on average, annual loads of 3.9 N lbs/acre, 0.7 P lbs/acre, and 33.1 S lbs/acre.

The delivery ratios for cropland and grass cover for each parcel n, $d^z_{n,crop}$ and $d^z_{n,grass}$, represent the proportion of each pollutant load type z delivered from the edge-of-stream to the Bay and are obtained from the CAST Source Data. Because the delivery factor varies by land-river segment, we use land-river segment area in each program-eligible cropland to obtain the area-weighted average of the delivery factor for cropland and grass cover. The delivery factor varies little between cropland and grass cover but varies significantly across pollutant type: 0.75 for N, 0.69 for P, and 0.34 for S for both cropland and grass cover. Choi et al. (2020) suggest per-pound social cost of pollutant loads in the Chesapeake Bay, m^z, in year 2015 values. We convert these values into 2020 values using CPI and obtain \$16.34/lbs for N, \$198.31/lbs for P, and \$0.40/lbs for S. The estimated annual direct benefits when converting cropland to grass cover are \$454.8/acre on average, which is the sum of \$251.3/acre (N), \$32.8/acre (P), and \$170.7/acre (S).

For the indirect benefits, each acre of riparian buffer installed is assumed to filter and reduce the pollutant loads from multiple upland acres that remain in cropland production. Following the assumption made by the EPA's Chesapeake Bay Program expert panel (Belt et al. 2014), we assume that each acre of riparian buffer has the capacity to filter and reduce loads at the efficiency rate for four cropland acres for N and two cropland acres for P and S (x^N=4 , x^P=2, x^S=2).

The efficiency with which grass buffers remove nutrients or sediment η^z_{nt} is assumed to grow over time as the grass cover establishes and matures. We use a Mitscherlich-Spillman type function to approximate this growth in the nutrient and sediment removal rates:

$$\eta^z_{nt} = \theta^z_n[1 - exp(-\psi(t+1))], \qquad (B.14)$$

where θ^z_n is the maximum removal rate for pollutant z and $\psi > 0$ is the rate at which pollutant removal grows over time.

We obtain the maximum rate θ_n^z using the efficiency rate of riparian grass buffers by pollutant type provided in CAST – Source Data. The average rates across 7,223 parcels are 31.1% for N, 41.4% for P, and 55.2% for S, with spatial variability across hydrogeomorphic regions. The parameter ψ is calculated under the assumption that the efficiency rate of grass buffer for each pollutant z, η_{nt}^z, reaches half of the maximum rate θ_n^z during the first year of establishment ($t = 0$):

$$\eta_{n0}^z = \theta_n^z[1 - exp(-\psi)] = \frac{1}{2}\theta_n^z. \quad (B.15)$$

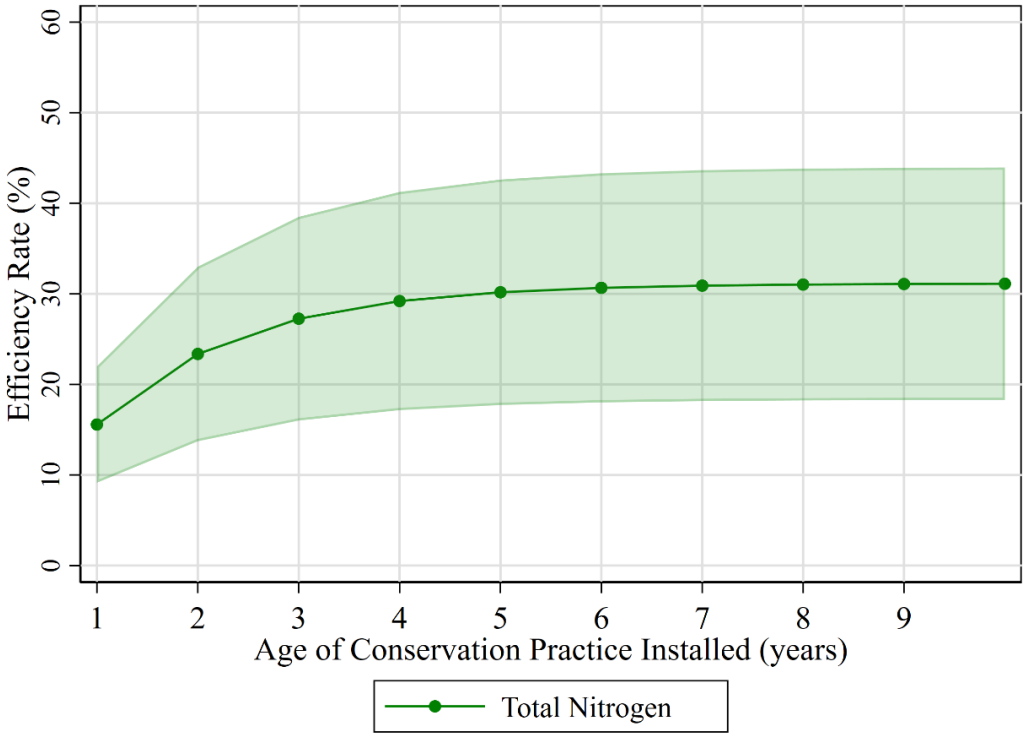
The parameter ψ is thus equal to $-ln(0.5)$. Then, the time profile of efficiency rate for the grass buffer can be obtained as follows:

$$\eta_{nt}^z = \theta_n^z\left[1 - exp\left(ln(0.5)(t+1)\right)\right] \quad (B.16)$$

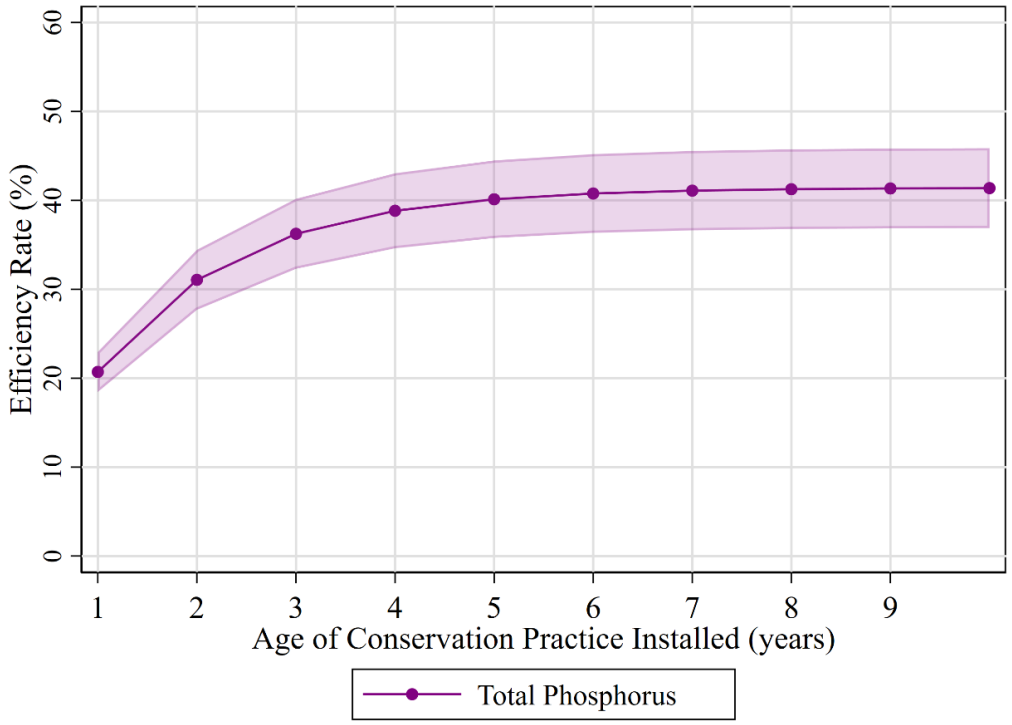
To estimate the indirect benefits, we first obtain the time profile of efficiency rate for the grass buffer using equation (B.16). Figure B1 presents the time profile of average efficiency rate of grass buffer across parcels by pollutant type with intervals of one standard deviation. The efficiency rate of the riparian buffer increases from 15.6% for N, 20.7% for P, and 27.6 for S in the first year to 31.1% for N, 41.4% for P, and 55.2% for S in year 10 as the grass buffer matures (Belt et al., 2014; Hairston-Strang, 2005). Finally, using equation B.13, we obtain indirect benefits of converting cropland into riparian grass buffers, which increases from $329.4/acre in the first year of the contract to $658.2/acre in year 10, on average.

Figure B1. Efficiency Rate of the Riparian Grass Buffer by Pollutant Type

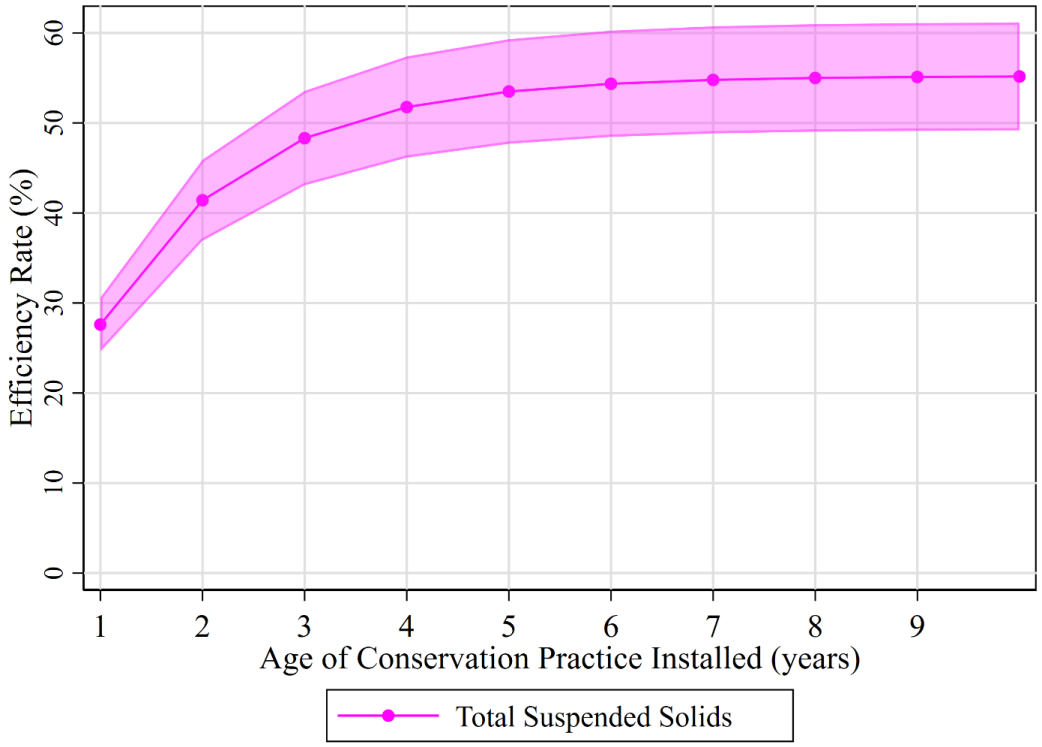
A. Efficiency rate of the riparian grass buffer – total nitrogen



B. Efficiency rate of the riparian grass buffer – total phosphorus

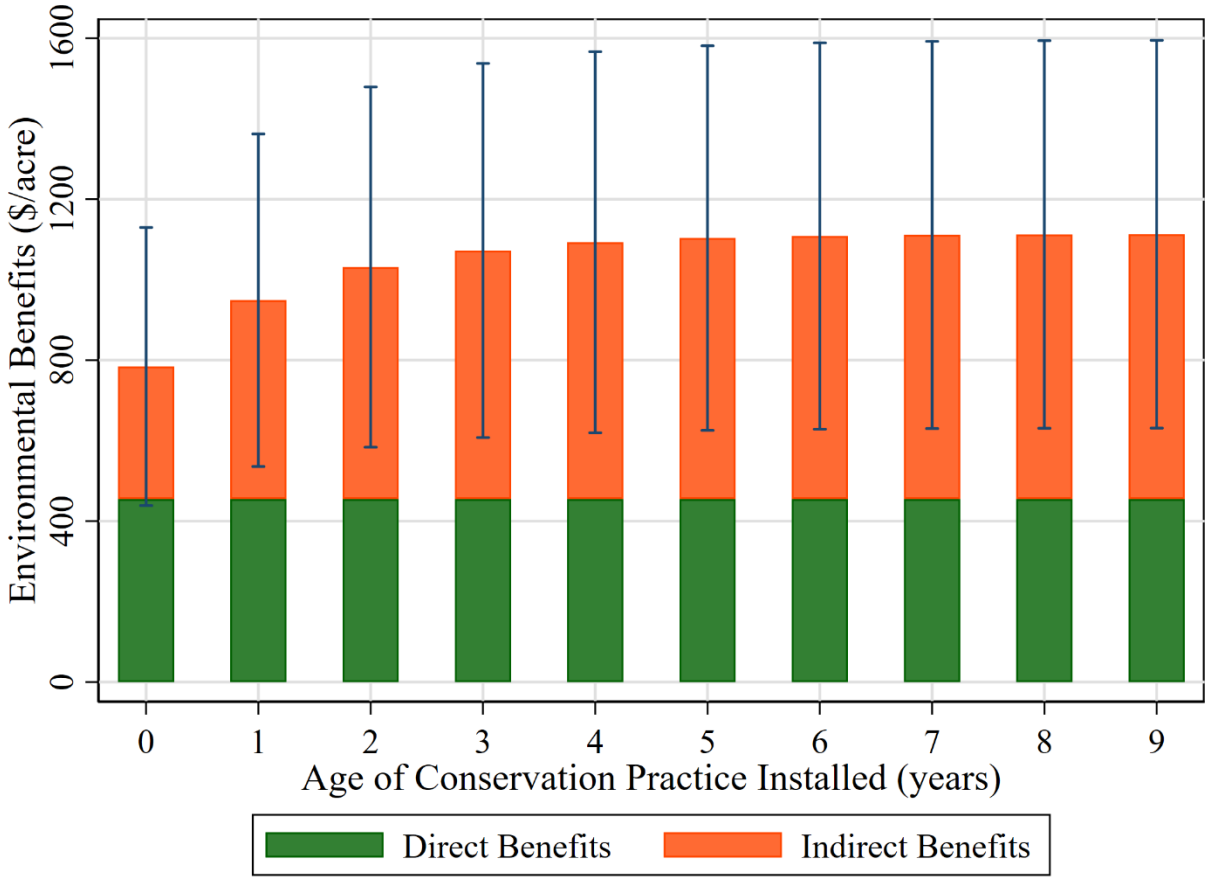


C. Efficiency rate of the riparian grass buffer – total suspended solids



Note: The graph presents the average nutrients and sediment removal rates of the newly installed riparian grassed buffer over time for the 7,223 parcels in the simulation. Intervals represent one standard deviation below and above the mean. The results are calculated based on the equation (B.16).
Source: Author's estimate based on Lowrance (1992), Fennessy and Cronk (1997), Hairston-Strang (2005), Simpson and Weammert (2009), Newbold et al. (2010), and Belt et al. (2014).

Figure B2. Time Profile of Annual Environmental Benefits of Converting Cropland to Grass Riparian Buffer



Note: The graph presents the average annual water quality benefits of converting cropland to the riparian grass buffer for 10 years across 7,223 parcels included in the simulation. Intervals indicate one standard deviation below and above the mean of total environmental benefits (direct + indirect benefits). The results are calculated based on the equations (B.12) and (B.13).

B3. Calculating The Opportunity Cost of Land

The numerical simulation analysis examines the 7,223 landowners with agricultural cropland parcels adjacent to waterbodies in Maryland. These parcels are considered potentially eligible for PES contracts that convert cropland into riparian grass buffer for a 10-year contract period. In this section, we explain the methodology to calculate the landowner n's time 0 expectation on annual crop returns, v_n, which represents the opportunity costs of program enrollment. To provide estimates on the parcel-specific annual crop returns in the riparian buffer zone, we adjust the statewide annual crop return π by incorporating two sources of spatial variation: (a) county-level soil rental rates ϕ_c and (b) parcel-level soil productivity κ_{nc} within the riparian buffer zone using the National Commodity Crop Productivity Index (NCCPI) from the USDA NRCS. Specifically, let $\bar{\phi}$ denote the average soil rental rate for cropland ϕ_c across all counties in Maryland and let $\bar{\kappa_c}$ denote the average crop productivity across all parcels in county c. The parcel-level expected crop return v_n is estimated as follows:

$$\hat{v}_n \equiv \pi \times \frac{\phi_c}{\bar{\phi}} \times \frac{\kappa_{nc}}{\bar{\kappa_c}}. \qquad (B.17)$$

where the statewide annual crop return π is multiplied by the ratio of the soil rental rate in county c to the state average $\phi_c/\bar{\phi}$ and the ratio of soil productivity in parcel n to the county average $\kappa_{nc}/\bar{\kappa_c}$. Below we provide a more detailed description of the step-by-step approach for calculating each component in equation (B.17).

State-level crop return (π)

We obtain state-level annual crop return π from 2021 Maryland Crop Budget. The net crop return is calculated as gross revenue less variable and annualized fixed costs for non-irrigated corn

production. Net crop return differs by tillage management practices. Both no-till corn and conventional-till corn have the same gross income of $720/acre but have slightly different variable costs $316.3/acre and $310.8/acre, respectively. Total fixed cost is lower for no-till ($125.3/acre) compared to conventional tillage ($182.9/acre). We exclude land rental rate ($98/acre) as our model considers the owner-operator who makes decisions on farm operations and enrollment in conservation programs. To incorporate different net crop return by tillage management practices, we calculate the acreage-weighted average of crop return of two tillage practices, where weights are approximately two-thirds for no-till and one-third for conventional tillage based on USDA NASS's 2022 Maryland Tillage Estimates. This yields the estimated statewide crop return π at $261.1/acre, which is then converted to $249.4/acre using CPI to obtain the value in 2020.

County-level crop return (ϕ_c)

Next, we incorporate spatial heterogeneity in expected annual crop returns across counties in Maryland. Recall that ϕ_c denotes the soil rental rate of cropland in county c and $\bar{\phi}$ denotes the statewide average of ϕ_c across all counties. Then, the ratio of ϕ_c to $\bar{\phi}$ measures the crop profitability of cropland in county c relative to all counties in the state. Using USDA NASS's cash rental rate for non-irrigated cropland in 2020, the county-level rental rate ϕ_c ranges from $28.0/acre to $167.0/acre for the 23 counties in Maryland, with the statewide average $\bar{\phi}$ at $84.2/acre.

Parcel-level crop return within the county (κ_{nc})

Lastly, we incorporate the spatially heterogeneous parcel-level crop return within each county. Specifically, we first identify the location of 100-foot riparian buffer zone in each parcel by

overlaying spatially explicit parcel boundaries obtained from Maryland Department of Planning with USGS National Hydrography Data. We then measure crop productivity in the riparian buffer zone using the NCCPI, provided in the USDA NRCS Soil Survey Geographic Database. The NCCPI measures potential productivity of a specific soil types for particular crops, taking into account production conditions such as climate, topography, and soil properties. This index is useful to compare relative crop profitability across agricultural parcels. The average parcel's area-weighted NCCPI for corn, incorporating all soil types with positive NCCPI in the 100-foot riparian buffer zone, is calculated to be 0.54 with a standard deviation of 0.13. The parcel's proportional deviation in soil productivity from the county average $\kappa_{nc}/\bar{\kappa}_c$ serves as a measure of parcel n's crop productivity relative to all parcels in the same county. Finally, this normalized measure is combined with the county's deviation in soil rental rate $\phi_c/\bar{\phi}$ and statewide annual crop return π in accordance with formula (B.17), yielding an average of \$281.3/acre with a standard deviation of \$116.1/acre. Overall, our approach incorporates both county-level and parcel-level heterogeneity in crop returns.

B4. Sensitivity Analysis: Interest Rate

Table B1. Summary of Simulation Results: Higher Interest Rate

Budget	Contract	Participation rate	Non-completion rate	Environmental benefits ($ million)	Program payments ($ million)	Penalty revenue ($ million)	Net program benefits ($ million)
$1M	Standard	2.4%	2.7%	10.1	1.0	0.0	9.1
	Optimal	2.3%	0.0%	10.4	1.0	-	9.4
$5M	Standard	9.0%	5.9%	36.0	4.7	0.1	31.3
	Optimal	8.5%	0.0%	38.0	5.0	-	33.0
$10M	Standard	16.5%	7.2%	63.7	9.4	0.2	54.5
	Optimal	15.8%	0.0%	68.0	10.0	-	58.0
$20M	Standard	29.8%	9.1%	109.9	18.4	0.5	91.9
	Optimal	29.0%	0.0%	119.2	20.0	-	99.2

Note: The table presents simulated outcomes of PES program that converts cropland into riparian grass buffer for a 10-year contract. The principal's cost of funding is set at 5 percent instead of 2.5 percent in the baseline.

Appendix C: Appendices to Chapter 3

C1. Calculating Carbon Sequestration Benefits of Riparian Forest Buffers

Modeling a carbon (C) trading program in our policy simulations requires an understanding of the potential for C sequestration by riparian forest buffers planted on agricultural cropland, defining the level of payments farmers could expect to receive for such C storage, as well as a characterization of the social costs associated with C emissions. In our biophysical modeling process, we construct parcel-specific estimates of C storage densities, which we then monetize using available estimates of recent carbon trading prices and the social cost of carbon.

Source of C Storage Data

The first goal is to construct a parcel-specific estimate of C storage that could be achieved through the planting of riparian forest buffers, q_{it}^{C}, where i indexes parcels and t indexes the year of contract. To start, q_{it}^{C} is defined on a per-acre basis, and can be thought of as a C storage density (quantity C / area). Multiplying this density by the total area enrolled yields a total C stock.

We characterize q_{it}^{C} by making use of newly available high-resolution raster data representing C storage in the northeastern United States (Ma et al. 2021, 2022a, 2022b). These data represent C storage growth trajectories of aboveground biomass (AGB) for the first 300 years of forest succession. Estimates of C storage densities in kg C / m^2 are given for each 30m x 30m grid cell in the data for each year. These data cover most of the northeastern United States, and were derived from a modeling process designed to estimate total contemporaneous AGB stocks for the states that make up the RGGI, a regional carbon dioxide (CO_2) emissions trading program in the

northeastern United States. Given the focus of our analysis, we limit our use of these data to the state of Maryland.

These data work well for us to characterize potential for C storage on parcels in our data for two primary reasons. The first is the dynamic nature of the question we seek to answer. Specifically, we are not concerned with aggregation exercises such as estimating current total AGB stocks across existing forested lands in Maryland. Our goal is to quantify the additional C that could be stored through the planting of new forest cover on land previously used as cropland near environmentally-sensitive waters. These data are uniquely suited to answer this question because they simulate the growth trajectories of AGB over time using the Ecosystem Demography (ED) v3.0 model (Ma et al. 2021, 2022a, 2022b). ED is a biophysical model that models the dynamic nature of plant growth and associated C storage. The ED-generated data we use represent the growth dynamics of AGB over time going "from bare ground to mature forest" (Ma et al. 2021). While the data give AGB growth estimates over 300 years, we are chiefly concerned with the growth in C storage that would occur in the first 15 years after planting to correspond with common contract lengths offered by programs like CREP in Maryland. Using these data allow us to estimate changes in C storage that could occur over such a 15 year period.

The second reason why these data work well for our purposes is the highly localized nature of the 30m C storage density estimates. Given that our study region and focus is on agricultural parcels in Maryland, we wish to use data that accurately characterize forest C storage potential in Maryland specifically, as opposed to regional, national, or global averages. As discussed above, these data were derived specifically from a modeling process intended to estimate total C sequestration potential for RGGI member states, which includes Maryland (Ma et al. 2021). The ED model relies primarily on spatial and temporal variation in three sets of inputs to generate AGB

estimates. These include local meteorological conditions (temperature, precipitation, humidity, etc.), atmospheric CO_2 concentrations, and soil characteristics (depth, water retention, etc.) The ED model therefore generates AGB estimates with a high-degree of local specificity, rather than relying on regional or national averages in model inputs that may mask important spatial heterogeneity.

Constructing C Storage Density Estimates

We calculate parcel-specific C storage estimates by overlaying shapefiles of the parcels we consider in our analysis with the Ma et al. (2022a) AGB raster data in each year. Each parcel i in our analysis is covered by multiple 30m grid cells from the raster data, indexed by j. Abstracting away from the time dimension momentarily, the AGB storage density for parcel i is calculated by taking an arithmetic mean of the storage densities in each grid cell for that parcel:

$$q_i^C = \sum_{j=1}^{J} q_{ij} \qquad (C.1)$$

This process can be repeated for each year in the raster data, yielding the year-specific AGB storage density estimate defined earlier, q_{it}^C. Our measures of C storage densities depend on certain assumptions. First, we must make an assumption about how to define the appropriate set of grid cells over which C density estimates are constructed. In a first approach, we make use of all grid cells falling within entire buffer area around streams on the parcels we consider in our analysis. By using this simple definition, we capture average C storage potential across the buffer area, which is where the new forest cover will be planted.

However, existing land uses and factors like soil quality that affect the ED model outputs have the potential to vary across buffer areas. We are primarily interested in understanding how AGB grows over time on land that is converted from cropland to bare ground for the purpose of installing new forest cover. The presence of existing forest, wetlands, or other land uses in the buffer area may be biasing the AGB estimates if we use the entire buffer area as the underlying land base. Therefore, we also conduct a sensitivity analysis in which calculate q_i^C using only land identified as existing cropland in Maryland. To do so, we make use of the high-resolution 1m land use data from the Chesapeake Conservancy (Chesapeake Bay Program, 2023). To do so, we overlay the Ma et al. (2022a) data with the Chesapeake Conservancy data and calculate land use proportions on each grid cell in the Ma et al. data. We then keep only grid cells in the Ma et al. (2022a) data that are entirely covered by existing cropland or hay/pasture land. We then overlay our shapefiles of parcels in the sample with the masked forest carbon raster data, and calculate the same arithmetic mean q_i^C, this time only on these "purely agricultural" grid cells j. We use all such grid cells on the entire parcel to construct the average, not just those in the buffer area. This is because in some cases buffer areas can be relatively small and may not contain many grid cells devoted to a single land use. Ultimately, constructing the average in this way gives us an average C storage density estimate defined using only the exact type of land cover that the forest riparian buffers would be installed on.

To this point, recall that we have defined C storage densities in each year in terms of kg C / m^2. We next need to make an assumption about the structure of the C quantities that agricultural landowners planting buffers would receive credits for under a trading program. Landowners could conceivably be paid for C storage in one of two ways. First, they could be paid for the total C stock that they store over the course of the 15-year contract period. This would represent "additional" C

storage relative to a baseline of no C storage given that the land would be used in cropland in its next alternative use. Using this assumption yields a single value for q that is not indexed over time by year t, as we have a single storage density value for parcel i in the final year of the contract, termed $q_i^{C,stock}$.

Alternatively, farmers could also be paid year-over-year for the increase in C stored relative to the year before, or the C flow. This would capture potential nonlinearities in C growth over time, while at the same time discounting payments for stored C in the future rather than crediting the farmer in the first year as under the stock assumption. Under this assumption, we return to indexing storage benefits by year t:

$$q_{it}^{C,flow} = q_{it}^{C} - q_{i,t-1}^{C} \qquad (C.2)$$

Recall that both $q_i^{C,stock}$ and $q_{it}^{C,flow}$ are still defined as densities. Total payments based on these quantities would be derived by multiplying $q_i^{C,stock}$ and $q_{it}^{C,flow}$ by the enrolled program area.

Monetizing Benefits and Costs

After characterizing C storage densities, we next need to monetize the benefits and costs associated with additional carbon storage. In the carbon trading program, we assume that landowners are issued one credit per metric ton of C stored by the forest buffers. We convert all C storage densities calculated previously from kg C /m^2 in the following way:

$$\frac{1\ kg\ C}{m^2} * \frac{4{,}046.86\ m^2}{acre} * \frac{1\ Mg\ C}{1{,}000\ kg\ C} = \frac{Mg\ C}{acre} \qquad (C.3)$$

We assume frictionless trading, i.e., landowners are able to find willing purchasers for all C credits that they receive. In this way, we are assuming a "best-case" scenario for carbon trading,

as landowners experience no transaction costs and complete certainty in payments, conditions unlikely to occur in actual carbon trading markets.

Define the price of a credit for a single metric ton of C stored as p_{mean}^{credit}. To parameterize this credit price, we make use of recent CO_2 allowance clearing prices in the RGGI market. While RGGI is a program primarily focused on reducing CO_2 emissions from the electricity sector, we use RGGI prices because a) it is well-established carbon market with trading activity dating back to 2008, b) allowance clearing prices are transparent and readily available (which is not the case for many nascent carbon markets), and c) is a regional program focused on the northeastern U.S., including our study region of Maryland. We first define a mean price for C credits in the year 2021 by taking the arithmetic mean of the 4 quarterly auction clearing prices for the year 2021, which is \$9.47/short ton CO_2. We then adjust the price in terms of metric tons, which is \$10.44/metric ton CO_2. Finally, we convert \$/metric ton CO_2 into its C equivalent, using the ratio of the molecular weight of C to CO_2: 12/44. This implies that there are 0.2727 tons of C in one ton of CO_2. Accounting for this ratio yields a final mean credit price p_{mean}^{credit} of \$38.28/metric ton C in 2021 dollars.

We also note that RGGI clearing prices have been rising since 2021 in real, not simply nominal terms. As a sensitivity analysis, we also parameterize p_{high}^{credit} by taking the arithmetic mean of the 4 RGGI clearing prices from 2022, which when adjusting for inflation back to 2021 dollars is \$12.46/short ton CO_2. Applying the same set of steps (adjusting for metric tons and C/CO_2 ratios) yields a value for p_{high}^{credit} of \$50.37/metric ton C in 2021 dollars. Ultimately, program costs c in a given year can be calculated under either scenario by multiplying the relevant p^C by the desired q_{it}^C value (either stock or flow):

$$c_{it} = q_{it} * p_{(low,high)}^{credit} \qquad (C.4)$$

We then characterize the social benefits of C storage by using the latest estimates of the social cost of carbon, or SCC (Carleton and Greenstone 2022, EPA 2023). Estimates of the SCC are generated through integrated assessment models that calculate the economic damage associated with an additional ton of CO_2 emitted into the atmosphere. Avoiding these emissions results in societal benefit. We fix a discount rate $r = 0.025$, and use the according SCC value of \$120/metric ton CO_2 in 2020 dollars to parameterize p_{mean}^{SCC}, the monetary value of the reduction of 1 ton of C. We use CPI data to inflation-adjust this value to 2021 dollars, and then convert to an equivalent C price using C/CO_2 molecular ratios, resulting in a value of \$460.72/metric ton C.

Most standard SCC estimates account for economic damage that occurs many years into the future. Our time-horizon is more limited in that we consider the benefits of keeping C out of the atmosphere over the course of a 15-year contract period. Therefore, we also parameterize p_{low}^{SCC}, where we adjust the SCC downwards to account for the fact that landowners may potentially remove forest cover after the contract is completed. To do so, we use a continuous time adjustment factor to adjust the SCC downwards to account for the 15-year period:

$$p_{low}^{SCC} = \frac{\$460.72}{ton\ C} * (1 - e^{-.025*15}) = \frac{\$144.07}{ton\ C} \qquad (C.5)$$

We specify payments to landowners and benefits under carbon trading in two ways: as upfront payment values and as equivalent annuity values spread out over the course of the 15-year contract period. First consider upfront payments. In the case of $q_i^{C,stock}$, landowners are paid once for the total stock that they generate at the beginning of the contract period. Therefore, this is also the upfront payment value. In the case of $q_{it}^{C,flow}$, landowners receive time-varying payments based on the flow of C from the previous year. In this case, we calculate the net present value (NPV) of this flow of payments over a 15-year period as the equivalent upfront payment that the landowner would receive using the standard formula:

$$NPV = \sum_{t=0}^{T} \frac{q_{it}^{C,flow} * p}{(1+r)^t} \qquad (C.6)$$

Then consider the annualized values. We take the upfront payment value and convert it to a constant annuity value (AV) that, when discounted back, is equal to the NPV upfront payment. We use the following formula that accounts for no discounting in the first-year:

$$AV = \frac{NPV * r}{(1-(1+r)^{-t}) * (1+r)} \qquad (C.7)$$

In the case that a parcel's C storage value is missing, we compute an area-weighted average of benefits for other parcels in the same county and assign that average to the missing parcel.

Bibliography

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.

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.

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.

Askari, H., & Cummings, J.T. (1977). Estimating agricultural supply response with the Nerlove model: A survey. *International Economic Review*, 257–292.

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

Babcock, B.A., Lakshminarayan, P.G., Wu, J., & Zilberman, D. (1997). Targeting tools for the purchase of environmental amenities. *Land Economics*, 325–339.

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.

Banerjee, Simanti, Timothy N. Cason, Frans P. de Vries, and Nick Hanley. 2017. "Transaction Costs, Communication and Spatial Coordination in Payment for Ecosystem Services Schemes." *Journal of Environmental Economics and Management 83*: 68–89.

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), 83–104.

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

Belt, K., Groffman, P., Newbold, D., Hession, C., Noe, G., Okay, J., Southerland, M., Speiran, G., Staver, K., & Hairston-Strang, A. (2014). *Recommendations of the Expert Panel to Reassess*

Removal Rates for Riparian Forest and Grass Buffers Best Management Practices, Chesapeake Bay Program.

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.

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.

Carleton, T., & Greenstone, M. (2022). A guide to updating the US Government's social cost of carbon. *Review of Environmental Economics and Policy*, *16*(2), 196-218.

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, A. (2003). The pursuit of efficiency and its unintended consequences: Contract withdrawals in the Environmental Quality Incentives Program. *Applied Economic Perspectives and Policy*, *25*(2), 449–469.

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.

Chesapeake Bay Program (CBP). 2019. Chesapeake Assessment and Scenario Tool (CAST). Chesapeake Bay Program Office.

Chesapeake Bay Program. (2023), Chesapeake Bay Land Use and Land Cover (LULC) Database 2022 Edition: U.S. Geological Survey data release.

Choe, C., & Fraser, I. (1999). Compliance monitoring and agri-environmental policy. *Journal of Agricultural Economics*, *50*(3), 468–487.

Choi, D. S., Ready, R.C., & Shortle, J.S. (2020). Valuing water quality benefits from adopting best management practices: A spatial approach. *Journal of Environmental Quality*, *49*(3), 582–592.

Claassen, R., Cattaneo, A., & Johansson, R. (2008). Cost-effective design of agri-environmental payment programs: U.S. experience in theory and practice. *Ecological Economics*, *65*(4), 737–752.

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.

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.

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.

Dumbrell, N. P., Kragt, M. E., & Gibson, F. L. (2016). What carbon farming activities are farmers likely to adopt? A best–worst scaling survey. *Land Use Policy*, *54*, 29-37.

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.

Environmental Protection Agency. 2023. Report on the social cost of greenhouse gases: Estimates incorporating recent scientific advances. Docket Id No. EPA-HQ-OAR-2021-0317.

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.

Feng, H., Kling, C.L., Kurkalova, L.A., Secchi, S., & Gassman, P.W. (2005). The Conservation Reserve Program in the presence of a working land alternative: Implications for environmental quality, program participation, and income transfer. *American Journal of Agricultural Economics*, *87*(5), 1231–1238.

Feng, H., Kurkalova, L.A., Kling, C.L., & Gassman, P.W. (2006). Environmental conservation in agriculture: Land retirement vs. changing practices on working land. *Journal of Environmental Economics and Management*, *52*(2), 600–614.

Fennessy, M.S., & Cronk, J.K. (1997). The effectiveness and restoration potential of riparian ecotones for the management of nonpoint source pollution, particularly nitrate. *Critical Reviews in Environmental Science and Technology*, *27*(4), 285–317.

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.

Fisher-Vanden, K., & Olmstead, S. (2013). Moving pollution trading from air to water: potential, problems, and prognosis. *Journal of Economic Perspectives, 27(1),* 147-172.

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.

FONAFIFO, CONAFOR and Ministry of Environment. (2012). Lessons Learned for REDD+ from PES and Conservation Incentive Programs. Examples from Costa Rica, Mexico, and Ecuador.

Fraser, R. (2002). Moral hazard and risk management in agri-environmental policy. *Journal of Agricultural Economics*, *53*(3), 475–487.

Fraser, R. (2013). To cheat or not to cheat: Moral hazard and agri-environmental policy. *Journal of Agricultural Economics*, *64*(3), 527–536.

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*.

Gardner, B. (1976). Futures prices in supply analysis. *American Journal of Agricultural Economics*, *58*(1), 81–84.

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

González-Ramírez, J., Kling, C. L., & Valcu, A. (2012). An overview of carbon offsets from agriculture. *Annual Review of Resource Economics*, *4*(1), 145-160.
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.
Guerrero, S. (2021). Characterizing agri-environmental policies: Towards measuring their progress. *OECD Food, Agriculture, and Fisheries Paper no. 155.*
Hairston-Strang, A. (2005). *Riparian forest buffer design and maintenance*. Maryland Department of Natural Resources Forest Service.
Hansen, L. (2007). Conservation reserve program: Environmental benefits update. *Agricultural and Resource Economics Review*, *36*(2), 267–280.
Hart, R., & Latacz-Lohmann, U. (2005). Combating moral hazard in agri-environmental schemes: A multiple-agent approach. *European Review of Agricultural Economics*, *32*(1), 75–91.
Hellerstein, D. (2017). The US Conservation Reserve Program: The evolution of an enrollment mechanism. *Land Use Policy*, *63*, 601–610.
Hellerstein, D., Higgins, N.A., & Roberts, M. (2015). Options for improving conservation programs: Insights from auction theory and economic experiments. *Amber Waves, February*.
Horowitz, J.K., & Just, R.E. (2013). Economics of additionality for environmental services from agriculture. *Journal of Environmental Economics and Management*, *66*(1), 105–122.
Howard, G., Zhang, W., Valcu-Lisman, A., & Gassman, P.W. (2023). Evaluating the tradeoff between cost effectiveness and participation in agricultural conservation programs. *American Journal of Agricultural Economics.*
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.
Johnston, R. J., Ndebele, T., & Newburn, D. A. (2023). Modeling transaction costs in household adoption of landscape conservation practices. *American Journal of Agricultural Economics, 105*(1), 341-367.
Johnston, R.J., Boyle, K.J., Adamowicz, W., Bennett, J., Brouwer, R., et al., 2017. Contemporary guidance for stated preference studies. *Journal of the Association of Environmental and Resource Economists* 4(2): 319–405.
Jones, D., & Fischbacher, T. (2018). After the Conservation Reserve Program: Economic decisions with farming and grazing in mind. In *Texas A&M AgriLife Extension Service*.
Karwowski, N. (2022). *Estimating the Effect of Easements on Agricultural Production*. National Bureau of Economic Research.
Kim, Y., Lichtenberg, E., & Newburn, D. A. (2024). Payments and penalties in ecosystem services programs. *Journal of Environmental Economics and Management, 126*, 102988.

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.
Kragt, M. E., Dumbrell, N. P., & Blackmore, L. (2017). Motivations and barriers for Western Australian broad-acre farmers to adopt carbon farming. *Environmental Science & Policy*, *73*, 115-123.
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.
Krinsky, I., Robb, A., 1986. On approximating the statistical properties of elasticities. The Review of Economics and Statistics 86, 715–719.
Lankoski J, Cattaneo A. (2010). Guidelines for Cost-Effective Agri-Environmental Policy Measures. Paris: OECD
Lankoski, J., Lichtenberg, E., & Ollikainen, M. (2010). Agri-environmental program compliance in a heterogeneous landscape. *Environmental and Resource Economics*, *47*(1), 1–22.
Lee, K.-H., Isenhart, T.M., & Schultz, R.C. (2003). Sediment and nutrient removal in an established multi-species riparian buffer. *Journal of Soil and Water Conservation*, *58*(1), 1–8.
Lewis, D. J. (2010). An economic framework for forecasting land-use and ecosystem change. *Resource and Energy Economics*, *32*(2), 98-116.
Lewis, D. J., Plantinga, A. J., Nelson, E., & Polasky, S. (2011). The efficiency of voluntary incentive policies for preventing biodiversity loss. *Resource and Energy Economics*, *33*(1), 192-211.
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.
Lichtenberg, E., (2017). The farm bill, conservation, and the environment, *American Enterprise Institute*. United States of America.
Lichtenberg, E., Newburn, D. A., & Wang, H. (2024). Designing Contracts for Payments for Ecosystem Services Programs. Working Paper.
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.
Lowrance, R. (1992). *Groundwater nitrate and denitrification in a coastal plain riparian forest*. (Vol. 21, No. 3, pp. 401-405). American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America.
Lynch, L., & Brown, C. (2000). Landowner decision making about riparian buffers. *Journal of Agricultural and Applied Economics*, *32*(1379-2016–113193), 585–596.

Lyon, D.J., & Holman, T. (2009). *Converting CRP to cropland in the Nebraska Panhandle*. Cooperative Extension, Institute of Agriculture and Natural Resources, University of Nebraska.

Ma, L., G. Hurtt, and R. Lamb. (2022a). Simulated Forest Aboveground Biomass Dynamics, Northeastern USA [Data set]. In *Environmental Research Letters*. Zenodo.

Ma, L., G. Hurtt, H. Tang, R. Lamb, E. Campbell, R. Dubayah, M. Guy, W. Huang, A. Lister, J. Lu, J. O'Neil-Dunne, A. Rudee, Q. Shen, and C. Silva. 2021. High-resolution forest carbon modelling for climate mitigation planning over the RGGI region, USA. *Environmental Research Letters* 16:045014.

Ma, L., G. Hurtt, L. Ott, R. Sahajpal, J. Fisk, R. Lamb, H. Tang, S. Flanagan, L. Chini, A. Chatterjee, and J. Sullivan. (2022b). Global evaluation of the Ecosystem Demography model (ED v3.0). *Geoscientific Model Development* 15:1971–1994.

Malik, A. S., Letson, D., & Crutchfield, S. R. (1993). Point/nonpoint source trading of pollution abatement: choosing the right trading ratio. *American Journal of Agricultural Economics*, *75*(4), 959-967.

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.

Maryland Department of Environment (MDE). (2017). Maryland trading and offset policy and guidance manual - Chesapeake Bay Watershed.

Mason, C.F., & Plantinga, A.J. (2013). The additionality problem with offsets: Optimal contracts for carbon sequestration in forests. *Journal of Environmental Economics and Management*, *66*(1), 1–14.

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

McIntosh, C.S., & Shumway, C.R. (1994). Evaluating alternative price expectation models for multiproduct supply analysis. *Agricultural Economics*, *10*(1), 1–11.

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.

Miao, R., Hennessy, D.A., & Feng, H. (2014). Sodbusting, crop insurance, and sunk conversion costs. *Land Economics*, *90*(4), 601–622.

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.

Natural England (2013). Environmental Stewardship Handbook Fourth Edition – January 2013.

Newbold, J.D., Herbert, S., Sweeney, B.W., Kiry, P., & Alberts, S.J. (2010). Water quality functions of a 15-year-old riparian forest buffer system. *Journal of the American Water Resources Association*, *46*(2), 299–310.

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.

Palm-Forster, L.H., Swinton, S.M., Lupi, F., & Shupp, R.S. (2016). Too burdensome to bid: Transaction costs and pay-for-performance conservation. *American Journal of Agricultural Economics*, *98*(5), 1314–1333.

Parrott, S.D., & McIntosh, C.S. (1996). Nonconstant price expectations and acreage response: The case of cotton production in Georgia. *Journal of Agricultural and Applied Economics*, *28*(1), 203–210.

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.

Pathak, S., Wang, H., and Adusimilli, N.C. (2024). Contract noncompliance in conservation programs: panel evidence from Louisiana, USA. *Agricultural and Resource Economics Review*.

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.

Peterson, J.M., Smith, C.M., Leatherman, J.C., Hendricks, N.P., & Fox, J.A. (2015). Transaction costs in payment for environmental service contracts. *American Journal of Agricultural Economics*, *97*(1), 219–238.

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

Price, E., Hollady, T., & Wainger, L. (2019). *Cost analysis of stormwater and agricultural practices for reducing nitrogen and phosphorus runoff in Maryland*. Prepared for Maryland Department of the Environment. UMCES Technical Report TS73019.

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.

Rabotyagov, S. S., Valcu, A. M., & Kling, C. L. (2014). Reversing Property Rights: Practice-Based Approaches for Controlling Agricultural Nonpoint-source Water Pollution When Emissions Aggregate Nonlinearly. *American Journal of Agricultural Economics*, *96*(2), 397-419.

Rabotyagov, S.S., Campbell, T.D., White, M., Arnold, J.G., Atwood, J., Norfleet, M.L., Kling, C.L., Gassman, P.W., Valcu, A., & Richardson, J. (2014). Cost-effective targeting of conservation investments to reduce the northern Gulf of Mexico hypoxic zone. *Proceedings of the National Academy of Sciences*, *111*(52), 18530–18535.

Raina, N., Zavalloni, M., & Viaggi, D. (2024). Incentive mechanisms of carbon farming contracts: A systematic mapping study. *Journal of Environmental Management*, *352*, 120126.

Ransom, J.K., Aakre, D.G., & Franzen, D. (2008). *Bringing land in the Conservation Reserve Program back into crop production or grazing*. Extension Service, North Dakota State University.

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.

Roberts, M.J., & Bucholtz, S. (2005). Slippage in the Conservation Reserve Program or spurious correlation? A comment. *American Journal of Agricultural Economics*, *87*(1), 244–250.

Rosch, S. (2021). Federal Crop Insurance: A Primer. *Congressional Research Service*, *R46686*.

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.

Sanderson, B.A., Quilkey, J.J., & Freebairn, J.W. (1980). Supply response of Australian wheat growers. *Australian Journal of Agricultural Economics*, *24*(2), 129–140.

Savage, J., & Ribaudo, M. (2016). Improving the efficiency of voluntary water quality conservation programs. *Land Economics*, *92*(1), 148-166.

Scarpa, R., Rose, J. M., (2008). Design efficiency for non-market valuation with choice modelling: How to measure it, what to report and why. *Australian Journal of Agricultural and Resource Economics* 52(3): 253–282.

Schatzki, T. (2003). Options, uncertainty and sunk costs: An empirical analysis of land use change. *Journal of Environmental Economics and Management*, *46*(1), 86–105.

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.

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.

Shortle JS, Ribaudo MO, Horan RD, Blandford D. (2012). Reforming agricultural nonpoint pollution policy in an increasingly budget-constrained environment. *Environ. Sci. Technol. 46(3):*1316–25

Shortle, J., & Horan, R. D. (2013). Policy instruments for water quality protection. *Annual Review of Resource Economics., 5*(1), 111-138.

Simpson, T., & Weammert, S. (2009). Developing nitrogen, phosphorus and sediment reduction efficiencies for tributary strategy practices: BMP assessment, Final Report. College Park, Maryland: University of Maryland. Mid-Atlantic Water Program. *University of Maryland, Mid-Atlantic Program, College Park, Maryland*.

Song, F., Zhao, J., & Swinton, S.M. (2011). Switching to perennial energy crops under uncertainty and costly reversibility. *American Journal of Agricultural Economics*, *93*(3), 768–783.

Stephenson, K., & Shabman, L. (2017). Can water quality trading fix the agricultural nonpoint source problem?. *Annual Review of Resource Economics, 9,* 95-116.

Stubbs, M. (2023). *Agricultural Conservation and the Next Farm Bill*. Congressional Research Service, R47478.

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

Suter, J. F., Poe, G.L., & Bills, N.L. (2008). Do agents respond to land retirement incentives? Evidence from the conservation reserve enhancement program. *Land Economics*, *84*(1), 17–30.

Sweeney, B.W., & Newbold, J.D. (2014). Streamside forest buffer width needed to protect stream water quality, habitat, and organisms: A literature review. *Journal of the American Water Resources Association*, *50*(3), 560–584.

Sweeney, B.W., & Newbold, J.D. (2014). Streamside forest buffer width needed to protect stream water quality, habitat, and organisms: A literature review. *Journal of the American Water Resources Association*, *50*(3), 560–584.

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.

Talberth, J., Selman, M., Walker, S., & Gray, E. (2015). Pay for Performance: Optimizing public investments in agricultural best management practices in the Chesapeake Bay Watershed. *Ecological Economics, 118,* 252-261.

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

Thompson, N. M., Hughes, M. N., Nuworsu, E. K., Reeling, C. J., Armstrong, S. D., Mintert, J. R., ... & Foster, K. A. (2022). Opportunities and challenges associated with "carbon farming" for US row-crop producers. *Choices*, *37*(3), 1-10.

U.S. Department of Agriculture, Economic Research Service (USDA, 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.

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

U.S. Department of Agriculture. (2023). Report to Congress: A General Assessment of the Role of Agriculture and Forestry in U.S. Carbon Markets Written in support of the Greenhouse Gas Technical Assistance Provider and Third-Party Verifier Program, October 2023

van Kooten, G. C., & Zanello, R. (2023). Carbon offsets and agriculture: Options, obstacles, and opinions. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, *71*(3-4), 375-391.

Vossler, C.A., Bergeron, S., Doyon, M., Rondeau, D., 2023. Revisiting the gap between the willingness to pay and willingness to accept for public goods. *Journal of the Association of Environmental and Resource Economists* 10(2): 413–445.

Wallander, S., Claassen, R., Hill, A., & Fooks, J. (2019). *Working Lands Conservation Contract Modifications: Patterns in Dropped Practices*. Economic Research Report No.262, Economic Research Service, US Department of Agriculture

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

Weinberg, M., & Claassen, R. (2006). Conservation Program Design: Rewarding Farm Practices versus Environmental Performance. *ERS Econ. Brief, 5*.

Weng, W., Morrison, M.D., Boyle, K.J., Boxall, P.C., Rose, J., 2021. Effects of the number of alternatives in public good discrete choice experiments. *Ecological Economics* 182: 106904.

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.

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, J., & Boggess, W. G. (1999). The optimal allocation of conservation funds. *Journal of Environmental Economics and management, 38*(3), 302-321.

Wu, J., Zilberman, D., & Babcock, B. A. (2001). Environmental and distributional impacts of conservation targeting strategies. *Journal of Environmental Economics and Management, 41*(3), 333-350.

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.