Additionality and Duration in Cover Cropping Incentives

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Abstract

From the USDA to private carbon sequestration companies, a wide range of organizations offer producers short-term incentives to adopt cover cropping and other environmentally beneficial practices. This paper provides a model of how adoption cost and long-term repeated costs and benefits of a practice connect short-term additionality and long-term program impacts. If participants vary by adoption costs and have identical long-term costs, then targeting more additional individuals will also target those with greater long-term impact. If they vary by long-term costs, long-term impacts are increasing in additionality as the program attracts fewer always-adopters, and then decreasing in additionality as the population shifts to those for whom the practice is always unprofitable. This paper also estimates the effects of 3-year EQIP cover cropping incentive contracts on cover cropping both during and after the contract. Using individual EQIP application data, this paper estimates a regression discontinuity across EQIP application scores that fall above and below the approval threshold for their application pool. Cover cropping during a contract is found to be 95% additional, in line with matching study estimates of the effects. The post-program effect estimates are imprecise but suggest substantial long-term effects on cover crop use. Heterogeneous treatment effects across regions and contract size suggest that the long-term impact of cover cropping incentives is decreasing in a group's additionality, complicating efforts to jointly target additionality and long-term impacts.

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1 Introduction

Agricultural producers shape the land's environmental health through the practices they choose. Different methods of planting, tilling, and managing weeds and pest can store or release carbon, pollute or preserve waterways, and foster or hinder biodiversity. Environmentally beneficial agricultural practices may provide enough financial benefits to be profitable on some farms while not on others, depending on a farm's economic and environmental circumstances (Wittwer et al., 2017). As such, ever since the Soil Erosion Service formed in 1933 to prevent the recurrence of the Dust Bowl, government has played a role in encouraging farmers to adopt soil-preserving practices (Turner et al., 2014). Today, the expanding market for carbon credits has also reached agriculture. These crediting programs pay for producers to adopt practices that increase the carbon sequestered in soil, such as reducing tillage or planting cover crops. Cover crops are planted during times when the ground would otherwise be left fallow, protecting the soil until the farmer kills the cover crop to make way for the cash crop. Cover cropping can control runoff and erosion (Laloy and Bielders, 2010), reduce water pollution (Kladivko et al., 2014), allow farmers to reduce the use of artificial fertilizers and herbicides (Schipanski et al., 2014), and increase the level of carbon sequestered in the soil (Poeplau and Don, 2015).

Conservation agriculture programs face some key challenges to creating long-term benefits, as improvements in soil quality can easily be reversed if a farmer reverts to their previous practices. Soil carbon includes multiple chemical forms, some of which remain unchanged for thousands of years and others that can degrade and release stored carbon within a decade if a farmer abandons their soil conservation practices (Dynarski et al., 2020). This problem cannot be solved by simply lengthening the duration of carbon contracts. farmers in the soil carbon credit market are uninterested in long-term contracts for practices, preferring the flexibility of shorter contracts, and would likely require unfeasible high payments to make longer contracts (Drechsler et al., 2017). Most soil carbon credit standards today offer farmers contracts lasting 5 to 30 years (Oldfield et al., 2022), and the USDA's long-running Environmental Quality Incentives Program (EQIP) provides incentives for 1 to 5 years after which a farmer cannot get another EQIP contract for the same practice on the same field (USDA NRCS, 2018).

However, the designers of these incentive programs often expect that providing short-term incentives may lead to long-term practice change. First, the short-term incentives may help farmers overcome short-term adoption costs. Cover cropping introduces new seed costs immediately but takes several years to improve the soil enough to bolster yields, so the practice may need three or more years to become profitable (Myers et al., 2019). Short-term incentives may also help farmers learn how beneficial a practice is for them, and how best to implement the practice in their area: what cover crop species to plant, when to plant it, and how and when to kill it. Farmers cite uncertainty around the economic benefits of conservation agriculture practices as a key barrier to implementing them (Arbuckle and Roesch-McNally, 2015; Conservation Technology Information Center, 2023; Gonzalez-Ramirez et al., 2015; Reimer et al., 2012). Accordingly, access to information about cover crops plays a strong role in practice adoption (Baumgart-Getz et al., 2012).

To understand the social benefit of these carbon market contracts and short-term incentive programs, we therefore must understand if or when short-term contracts lead to long-term practice changes. Understanding the duration of practice change has important implications for the cost-efficacy of incentives and interventions. If farmers only need financial incentives to get through the initial costs of adoption and generally continue the practice afterwards on their own, then a few year's spending in support may create decades of benefits. On the other hand, where practices never become profitable to the point that farmers choose to sustain them on their own, a program may only provide benefits for as long as it continues payments. I introduce a model that provides insights into the relationship between short-term additionality and long-run impacts, driven by the underlying adoption costs and long-term costs that program participants face. Additionality is the degree to which a program creates behavior change compared to what participants would have done in the business-as-usual case. If all participants in a cover cropping program were already planning to cover crop, the program will have no additionality; if none of them would have done so, the program is completely additional. Change must be both additional and persistent to create substantial reductions in environmental damages, particularly in regards to nature-based solutions for climate change. A low additionality program creates little to no benefit in the short or long run unless it is cheap enough and widespread enough to compensate for the small individual impact. The level of additionality is estimated to vary widely across agricultural practices (Mezzatesta et al., 2013; Pannell and Claassen, 2020). Low practice duration would mean a high risk of rerelease of carbon, increasing the optimal ex ante discounting rate of temporary storage (Lötjönen et al., 2024; Murray et al., 2006). In the literature, these two problems are often discussed as separate concerns.

In this model, I provide a framework suggesting that the two problems can be traced to the same economic fundamentals. Participants with higher adoption costs and/or annual costs are more likely to be additional, but they are more likely to persist with the practice post-contract when a practice is at least slightly profitable to maintain in the long run. Thus, if potential participants differ by adoption costs and share the same long-term costs, targeting the "most additional" participants will also target those with higher long-term impact. However, if potential participants differ mostly by long-term costs, the "least additional" participants will be always-adopters for whom the payment makes no difference, and the "most additional" participants will be those with high long-term costs who will be quick to drop the practice after payments end. In this case, targeting the "moderately additional" participants for whom the practice is near the edge of profitability will have the highest long-term impact, even if this group has lower levels of short-term additionality. This framework thus simplifies the difficult-to-estimate metrics of additionality and long-term impact into two concrete questions: how large is the adoption barrier to a practice? And how costly is the practice to maintain? Encouraging joint consideration of short-term and long-term impact can help programs better optimize their targeting of participants.

I empirically explore this question in the context of EQIP, focusing on EQIP contracts for cover cropping. Founded in 1996, EQIP is the largest and longest running program providing incentives for conservation on working lands nationally, contracting with at least thirty thousand farmers per year from 2014 to 2024 (NRCS, 2024). With access to the USDA's ProTracts database of EQIP applications, I use a regression discontinuity around EQIP application scores to compare cover-cropping rates of barely-successful and barely-unsuccessful EQIP applicants.

I find that receiving an EQIP cover-cropping contract increased cover cropping rates among successful applicants by 95% during the contract period. This indicates that 95% of EQIP cover cropping contracts are additional, meaning that the farmer would not have planted a cover crop without the EQIP contract. Numerous papers have attempted to estimate the additionality of cover cropping payment programs, often using matching approaches (Mezzatesta et al., 2013; Claassen et al., 2018; Sawadgo and Plastina, 2021), modeling of adoption costs (Lichtenberg et al., 2018; Fleming et al., 2018), or county-level estimations (Park et al., 2023) that do not control for whether a producer has applied for or expressed interest in the conservation program. Rosenberg et al., 2024 provides an instrument that is clearly exogenous to producer interest, using a regression discontinuity across areas eligible and ineligible for expanded EQIP cover crop funding through the National Water Quality Initiative. They find that most of the impact of the NWQI on cover cropping comes from increased cover cropping on additional lands under EQIP contracts. However, they cannot control for the other channels through which the NWQI can impact cover cropping, such as increased funding for technical education and support, and increased EQIP funding for practices such as reduced tillage that are complementary to cover cropping. Accessing the EQIP application database allows this paper to provide a unique regression discontinuity estimate that minimizes room for omitted variable bias. The resulting 95% additionality estimate for cover crops is similar to the 80% and higher cover crop additionality estimates found in the bulk of the literature (Claassen et al., 2018; Fleming et al., 2018; Mezzatesta et al., 2013; Rosenberg et al., 2024), though it is higher than Sawadgo and Plastina, 2021's estimated 54% additionality for cover cropping in Iowa.

This paper also finds that EQIP seems to substantially increase long-term cover-cropping, though estimates are imprecise. Since the literature on cover crop additionality to date has largely focused on the during-contract effect, this long-term effect is a unique contribution to the cover cropping literature, and joins a larger conversation about hysteresis effects in environmental programs. After the expiration of an CRP contract, FIX CITE Rosenberg et al., 2022 finds that most fields revert to previous practices at high rates. Environmental programs seem able to create substantially durable change in many cases: Wallander et al., 2017 find that EQIP-induced changes in tillage do persist well beyond the contract period, and 66% of land retired through the Conservation Reserve Program remains as grassland in the 6 years after the program expiration (Barnes et al., 2020).

I test how this relationship between additionality and long-term impact appears in the case of cover cropping. Breaking out the population by region and operation size, I find that that a group's additionality is inversely correlated to its long-term impact. This suggests that targeting the most additional populations for cover cropping contracts would decrease the long-term benefits from the program.

In this paper, I first discuss the EQIP program and the data used in this paper. I then provide the model of the farmer's practice adoption and persistence decisions. I then explain the regression discontinuity methodology, and the present the results in the following section.

2 Data and Setting

2.1 The EQIP Program

This paper's analysis focuses on the USDA's Environmental Quality Incentives Program (EQIP). Established in the 1996 Farm Bill, the program offers educational, technical, and cost-share incentives to agricultural producers adopting environmentally beneficial practices on working lands. It was first authorized to spend $1.2 billion over 7 years, and has been renewed and expanded in every Farm Bill since.

Producers can apply for assistance with adopting practices that reduce water or air pollution, conserve water, control soil erosion, or protect habitat for at-risk species (Stubbs, 2011). EQIP has historically funded many key greenhouse-gas-emission-reducing practices, such as reducing tillage and planting cover crops, for their value in reducing soil erosion as well as air and water pollution. The Inflation Reduction Act of 2022 substantially increased funding specifically for emission-reducing practices. Cover cropping is EQIP's most commonly funded practice, drawing $504 million in payments made between 2017 and 2022 (Environmental Working Group, 2023).

In an EQIP contract, a producer receives a payment for performing certain agreed-upon conservation actions. The state-level Natural Resources Conservation Service (NRCS) office chooses the size of the incentive for each eligible practice. The payment amount is set to cover a maximum of 75% of the expected direct costs of implementing a practice in that state and up to 100% of the expected revenue to be lost through reduced output, when applicable (USDA NRCS, 2018). The producer receives the payment once the USDA certifies they have implemented the practice. For practices like cover crops or reduced tillage that must be repeated annually, the EQIP contract requires farmers to continue the practice for one to five years[1], and the producer is paid a partial payment each year once the USDA has confirmed they completed the practice that year.

[1] The 2018 Farm Bill, which covers some contracts that would begin but not end in my study period, expanded the maximum contract length to 10 years (USDA NRCS, 2018)

To participate in EQIP, producers must go through an application process. Acceptance rates have varied widely across years from 25% to 45%, reflecting year-to-year variation in EQIP funding and in application numbers (Happ, 2021). Upon receiving an application, the NRCS first checks for application completeness and program eligibility. Applications are submitted into pools, and eligible applications are ranked and funded within these pools. The State Conservationist's office in each state defines the pools, and often group applicants by environmental concerns addressed, geographic area, beginning and socially disadvantaged producers, or type of crop or livestock produced (USDA NRCS, 2018). The State Conservationist also chooses how much of the year's EQIP funding to place into each pool to best meet identified state-level needs while also following federal USDA requirements on elements like the share allocated to crop versus livestock producers.

Within the pools, applications are funded in order of their ranking score. Applications receive more points for practices with higher environmental impact, whether they address the NRCS's key program priorities, and also if the land has characteristics like highly erodible soil that make addressing a concern particularly urgent. Applications are also scored on cost-effectiveness (USDA NRCS, 2018). Once applications are scored and ranked, the USDA funds each application in a pool from highest scoring to lowest until they run out of funds. The remaining applicants are deferred for consideration until the next year, when they can choose to resubmit their application as is, or they may cancel or modify the application. These deferred applications must then compete against the next year's pool, and again may or may not be funded.

2.2 Contract and Applicant Data

Data on successful and unsuccessful EQIP applicants comes from the USDA's ProTracts database, which tracks contracts for NRCS programs including EQIP and CSP from the initial application through the final payments. For each application, ProTracts records the practices covered, the application's funding pool assignment and score, and the contract's status as it moves through the application dataset. ProTracts also includes some geographic data. ProTracts collects a standardized USDA tract number, farm number, and planning land unit number to facilitate matching to individual farms and fields.

Combining the data from 2004 to 2022 produces information on 1.49 million unique applications, with summary statistics reported in Table 1. 53% of those have reported pool affiliations and scores, and 18% of these are unsuccessful applications. Cover crops are one of the most common practices, and are part of 10% of applications. The mean application expects $30,000 in payments and impacts 335 acres of land. 55% of applications include information on which practices the contract would cover, which is not always imputed into ProTracts until an application becomes an active contract. Among those, 10% of contracts include cover cropping.

The dataset for this analysis is compiled from annual system pulls from 2004 to 2022, providing a snapshot of contracts that are active or in the application

Table 1: ProTracts Applications Summary Statistics

VARIABLES	(1) N	(2) mean	(3) sd
Contract accepted	1,490,199	0.590	0.492
Share of contract practices certified	1,490,199	0.373	0.461
Ranking score	796,205	523	5,057
Estimated payment ($)	823,423	30,038	1,104,996
Acres treated	1,061,707	335	6,039
Conservation cropping in contract	832,059	0.039	0.192
Cover cropping in contract	835,454	0.100	0.300
Reduced tillage in contract	831,103	0.011	0.105
No-till in contract	832,181	0.044	0.205

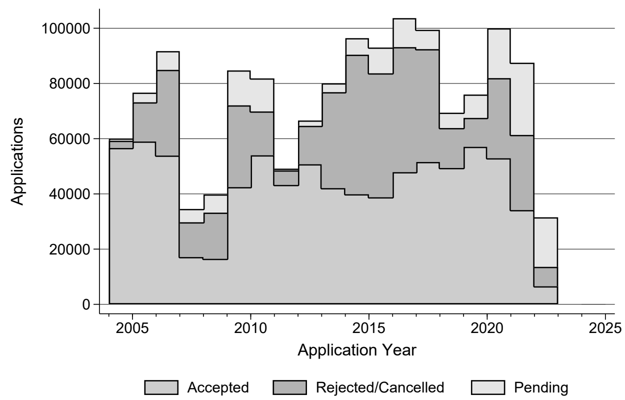
process that year. The exact implementation of these data pulls varied across years. Unsuccessful applications were omitted from some years of the data pulls, and the share of unsuccessful applications included may vary within years as well. As Figure 1 shows, this results in the number of deferred or canceled applications caught in the pull varying widely across years, particularly in 2011-2013 and 2019-2020, which I therefore omit from my analysis.

To manage the differential missingness created by these omissions, I identified the years where the data pull included a smoother distribution of successful and unsuccessful applications across the score margin, since this discontinuity may be representative of data issues. Figure 2 shows the sharp discontinuity in application counts across the score cutoff, a result of these missing applications. The results in Figure 2b show that after omitting applications originally submitted in the low-quality years of 2011-2013 and 2019-2020 and the similarly identified states of most concern, this discontinuity still exists but is somewhat smoothed.

2.3 Practice Data

To track the practices implemented on individual parcels, I use two USDA datasets: the Crop Acreage Reporting Database (CARD) from the FSA and the Agricultural Resource Management Survey (ARMS) from the ERS/NASS. CARD compiles data from Form 578, which all agricultural producers must file annually to participate in USDA programs, including insurance or subsidies. Farmers must report what crops they are planting and whether the crop is for harvest, grazing, or cover only. The dataset provided for analysis includes data on 23.6 million fields annually from 2013 to 2019, 855 thousand of which I match to ProTracts cover cropping applications. CARD-reported cover cropping rates stayed fairly even from 2013 to 2019, with 3.5 to 4.5% of fields using a cover

Figure 1: ProTracts Applications From 2004 to 2023



crop annually as depicted in Figure 3.

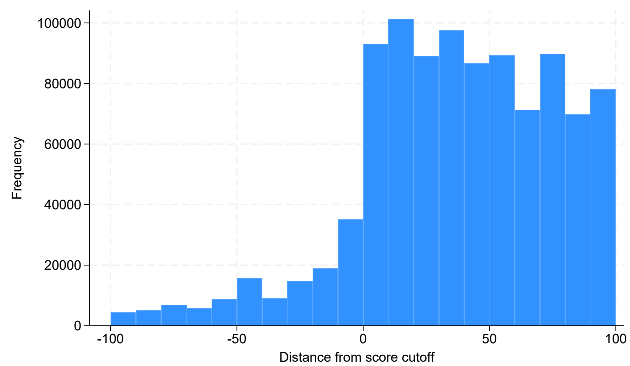
From this dataset I construct a measure of cover cropping in line with the broad definition used in current USDA analysis of CARD (Pratt et al., 2023). I classify a field as cover cropping if it reports a cover only planting or if it reports a planting that is not for grain or silage as a second planting after a cash crop. Since farmers may only report one purpose for each crop, this broad definition captures plantings that are serving the role of cover crops while also fulfilling other uses, such as grazing. In addition, in my main measure, I classify fields with an active EQIP cover cropping contract are implementing cover cropping. This corrects for underreporting through Form 578 among EQIP participants. Very few active EQIP cover crop participants report a cover only crop through Form 578, possibly because they have already reported the cover crop to the USDA through the separate channel used for EQIP reporting. Since 95% of farmers under active contract complete the practices and get payment, this assumption will not substantially overestimate the cover cropping rate for this group.

A key concern with this measure is that farmers other than EQIP participants have also historically underreported non-cash crops on Form 578. The USDA has long asked that farmers report all plantings through Form 578, but farmers only need to report their cash crop plantings to receive full insurance eligibility. Before 2021, they received no incentives or disincentives for accurately reporting cover crops. As such, CARD estimated much lower rates of cover cropping than other data sources such as windshield surveys (Pratt et al., 2023). Therefore, this paper's estimates may be an upper bound on the additionality of EQIP cover cropping and a lower bound on EQIP's long-term effect.

Going forward, I plan to correct this by examining effects in the years 2021 and beyond, when reporting improved after the Pandemic Cover Crop Program introduced a $5 per acre insurance premium discount for farmers that planted

Figure 2: Density of Applications Near the Cutoff

(a) Scores near the Threshold: All Merged Data



(b) Scores near the Threshold: Good States/Years

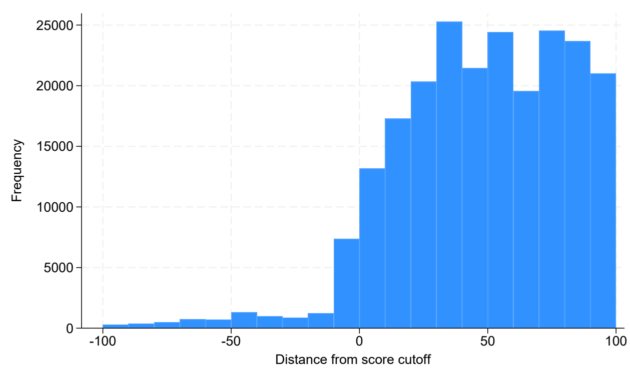


Figure 3: Cover Cropping in CARD

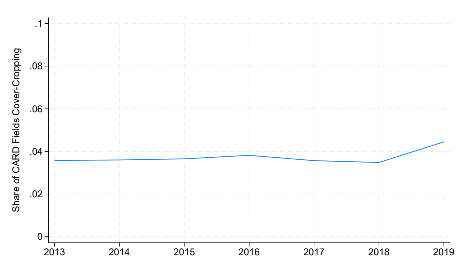
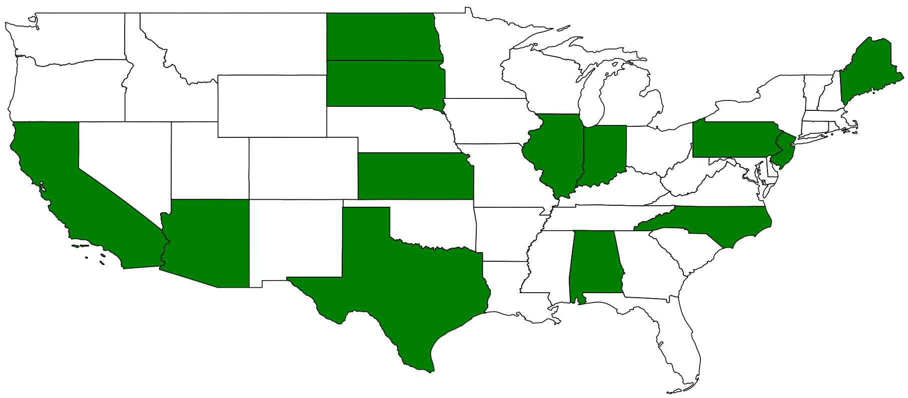


Figure 4: States Included in Analysis



and reported a cover crop. This $5 incentive is fairly modest compared to the $30-60 EQIP payments (Myers et al., 2019), and was intended primarily to provide additional pandemic-era support to farms using this socially beneficial practice. However, it dramatically increased reporting of cover cropping into line with cover cropping estimates obtained through other methods (Pratt et al., 2023), and the habit of reporting cover crops through form 578 seems to have sustained itself even after the incentives ended in 2022. This analysis will be possible once the CARD data for 2020 and beyond is panelized for analysis, enabling data linkages.

2.4 Linking CARD and ProTracts

To follow the outcomes of these ProTracts applications over time, I use USDA Planning Land Units (PLU) and Common Land Unit (CLU) identifiers of the field to merge ProTracts to the CARD crop planting data. As part of the application process, the USDA requires applicants to include the PLU information that will let the USDA identify the relevant fields. Most commonly, the PLU field, county, and tract is the same as the USDA CLU that identifies fields in CARD. However, this use of CLUs for PLUs varies across states. 27% of applications have clearly unmergeable field identifiers without numbers, and 60% of applications have PLU numbers that do not actually match to a USDA CLU.

To manage this missingness, I focus my analysis on 13 states that most commonly use CLUs in ProTracts and thus best merge to CARD, depicted in Figure 4, and that merge significant numbers of both successful and unsuccessful applications. For the states and years of focus, 72% of ProTracts fields have location data, and 52% of those merge to a parcel in CARD, resulting in 38% of entries matching. After narrowing down this matched sample to those with scores near the cutoff, I use 140,000 matched fields in my main regressions.

3 Model

In designing EQIP, the USDA faces a policy problem common to many government programs. Through EQIP, the USDA uses a short-term, voluntary incentive program to induce a behavior change that will provide social benefits. This behavior continues to provide a stream of benefits as long as it is sustained, and stops if the practice reverts. Calculating the total benefit of the program requires the answers to three questions. The first is additionality: during the program's duration, how much does it change participants' behavior from what they would have done otherwise? The second is hysteresis: after the program ends, how much of this behavior change continues? The final element is the translation from behavior change into environmental benefits: among the people who change their behavior, how much environmental impact in terms of carbon stored or pollution averted will their actions create?

A policymaker developing such a program must consider these factors as they decide which populations they wish to target, how much they will offer in payments, and whether they will allow previous participants to re-enroll. In this model, I link a participant's additionality and hysteresis to a pair of underlying factors: the short-term cost of adoption, and the long-term opportunity cost (or benefit) of continuing the practice. Potential participants may vary widely in these short-term and long-term costs, and those costs impact both the additionality and duration components of a contract's effects.

In this section, I first model the farmer's practice adoption decision as a function of adoption costs, long-term practice costs, and a shock to practice profitability. Next, I discuss how the hysteresis/additionality relationship differs depending on whether farmers vary by adoption cost or by long-term costs. I then explore how this relates to the program's cost of contracting. Finally, I discuss some extensions of the model.

3.1 The Farmer's Adoption Decision

This section establishes how a farmer will behave with or without a contract, which allows estimation of a their additionality under contract. In this model, a farmer who is not under contract must decide in each time period whether to take a socially beneficial action $x_t = 1$ that produces a social benefit e, or to use a conventional practice $x_t = 0$ that produces no social benefit. If under contract, the farmer must set $x_1 = 1$, but may then freely choose their practice in subsequent periods. In this paper's case, the beneficial action is cover cropping. The farmer's profit in a period t is

$$\begin{aligned} \pi_{kt}(X_{kt}, \epsilon_t) =& b_{0k} \text{ if } x_{kt} = 0 \\ & b_{1k} - a_k D(x_t > x_{t-1}) + \epsilon_t \text{ if } x_{kt} = 1 \end{aligned} \tag{1}$$

X_{kt} is the history of practices on field k through time t, b_{xk} is the constant average profit for practice x, $a_k \geq 0$ is the adoption cost of cover cropping. ϵ_t is a time-variant shock in the profitability of cover cropping, with $E[\epsilon_t] = 0$.

The farmer learns ϵ_t before they choose period t's practice x_t. I assume that the farmer is risk-neutral. They therefore choose their practices to maximize $E[\sum_t (1-r)^{t-1}\pi_{kt}(X_{kt}, \epsilon_t)]$, the risk-neutral expected profits discounted at rate r. Here, I explore a simple two-period setup, so the farmer chooses x_1 to maximize $\pi_{k1}(X_{k1}, \epsilon_1) + (1-r)E[\pi_{k2}(X_{k1}, \epsilon_2)|x-1]$. The farmer has not cover cropped before, so $x_0 = 0$ and the farmer has not yet paid the adoption cost. In this case, the farmer's period 1 cover cropping decision will depend on three things: the adoption cost a_k, the long-run cost difference $\Delta b_k = b_{0k} - b_{1k}$, and the profitability shock ϵ_k. The farmer will choose $x_1 = 1$ if

$$\epsilon_1 > \Delta b_k + a_k - (1-r)\Delta E[\pi_{k2}] \tag{2}$$

where $\Delta E[\pi_{k2}] = E[\pi_{k2}|x_1 = 1] - E[\pi_{k2}|x_1 = 0]$, the expected increase in period 2 profits from having cover cropped and paid the adoption cost in period 1. When $x_1 = 1$, the farmer chooses $x_2 = 1$ so long as $\epsilon_2 > \Delta b$. When $x_1 = 0$, the farmer cover crops only if $\epsilon_2 > \Delta b_k + a_k$. The farmer's total change in expected profits from adopting in period 1 is therefore

$$\begin{aligned}\Delta[\pi_{k2}] =& P(\Delta b_k < \epsilon_2 < \Delta b_k + a_k)(\Delta b_k + E[\epsilon_2|\Delta b_k < \epsilon_2 < \Delta b_k + a_k]) \\ &+ a_k P(\epsilon_2 > \Delta b_k + a_k)\end{aligned} \tag{3}$$

Two terms drive this change in expected period 2 profits. The first term is the difference in profits created by the farmer choosing to cover crop in period 2 when $x_1 = 1$ when they would not have if $x_1 = 0$. The second is the farmer's higher profits when the positive shock to cover cropping ϵ_2 is large enough that they choose to cover crop whether $x_1 = 1$ or 0.

The expected probability of additionality of Period 1 cover cropping is therefore

$$Additionality(a_k, \Delta b_k) = P(\epsilon_1 < \Delta b_k + a_k - (1-r)\Delta E[\pi_{k2}]) \tag{4}$$

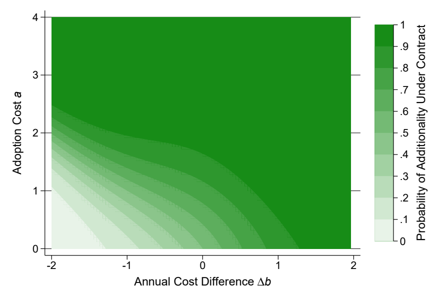
Figure 5a models additionality of cover cropping with $\epsilon \sim N(0,1)$. Cover cropping is less likely when adoption costs are higher and when cover cropping provides lower annual profits, so expected additionality is increasing in both a and Δb. If a farmer faces high adoption costs and does not expect to see a long-term annual profit, they are very unlikely to adopt a practice on their own, so an incentive should substantially change their behavior while under contract.

Behavior change under contract is not guaranteed to translate into continued behavior change post-contract. If a farmer cover crops in period 1 and pays the adoption cost, cover cropping will be profitable in period 2 whenever $\epsilon_2 > \Delta b_k$, while if the farmer did not cover crop in period 1, they will cover crop only if $\epsilon_2 > \Delta b_k + a_k$. So

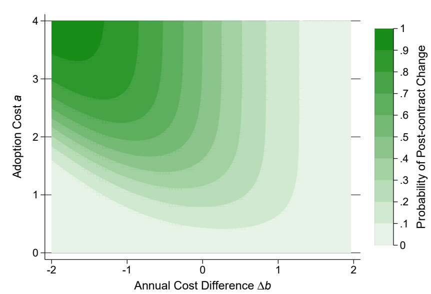
$$LongTerm(a_k, \Delta b_k) = Additionality(a_k, \Delta b_k) * P(\Delta b_k < \epsilon_2 < \Delta b_k + a_k) \tag{5}$$

Therefore, the period 2 impact from a period 1 contract will be the first-period additionality times the probability that a period 2 cover crop would be profitable only if the farmer already invested. This equation shows that for a contract to have long-term effects, two conditions must hold. First, the contract must

Figure 5: Contract Impacts on Cover Cropping Over Time



(a) During-Contract Additionality of Cover Cropping



(b) Post-Contract Change in Cover Cropping have changed their during-contract behavior, so $Additionality(a_k, \Delta b_k) > 0$. Equation 4 shows that this is more likely when the adoption cost or annual costs of the practice are higher. Second, having paid the adoption cost must meaningfully impact whether cover cropping is profitable in some states, so $P(\Delta b_k < \epsilon_2 < \Delta b_k + a_k) > 0$. This term is strictly increasing in the adoption cost: if $a = 0$, then past cover cropping experience has no impact on its future profitability, and a short-term contract does not impact later choices. However, its relationship to the annual cost Δb is more ambiguous. If Δb is so large that farmers would almost always choose to cover crop or so small that they would never wish to cover crop, the adoption cost would not weigh as heavily in their decision. It's the farmers for whom cover cropping teeters on the edge of profitability, the farmers for whom Δb is slightly below 0, for whom $P(\Delta b_k < \epsilon_2 < \Delta b_k + a_k)$ will be the largest. Figure 5b shows how this varies across Δb and a.

Figure 5b demonstrates that long-term behavior change increases in a similarly to additionality, but differs in its response to annual costs. When adoption costs increase and annual costs remain fixed, additionality and long-term benefits both increase, as Figure 6b shows. On the other hand, long-term impacts are increasing and then decreasing in the annual cost of cover cropping. Figure 6b traces a curve of additionality when long-term benefits vary and adoption cost a is a positive constant. When cover cropping is particularly profitable in the long run, farmers are likely to adopt cover cropping in period 1 even in absence of the contract, as the low additionality on the left side of Figure 6b demonstrates. Moving right on the graph as the the annual cost of cover cropping increases, rising first-period additionality increases the impact on second-period behavior.

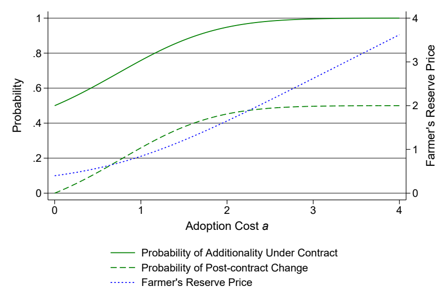
However, as we approach $\Delta b = 0$, the tipping point of long-term profitability, increasing Δb becomes associated with lower long-term impacts. As additionality approaches 1, $P(\Delta b_k < \epsilon_2 < \Delta b_k + a_k)$ begins decreasing because it becomes increasingly unlikely that a farmer would ever find cover cropping profitable without support. Getting a farmer past the adoption cost hurdle no longer matters when the annual profit losses are large enough to discourage cover cropping on its own.

This means that if a policymaker targets participants or evaluates programs based only on their short-term additionality, whether this maximizes total environmental benefits will depend on whether potential participants vary more by long-term or adoption cost. If adoption cost is the primary driver, the higher additionality participants will also have the greatest long-run benefit (or, if the practice is unprofitable for most to sustain in the long run, will at least be no worse.) On the other hand, if long-term costs vary, pushing for the "most additional" short-run participants may lead a policymaker to target the farmers who simply will not sustain a practice after the end of payments.

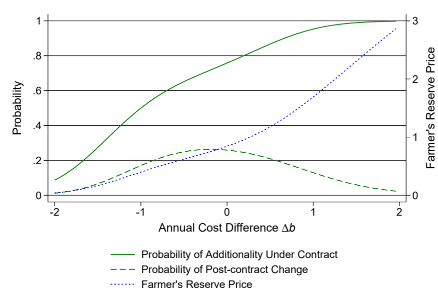
3.2 Contract Cost

Farmers with different values of a and Δb will also differ in the size of contract payment p needed to induce participation. Combining the payout structure

Figure 6: Exploring The Effect of Cost Variation

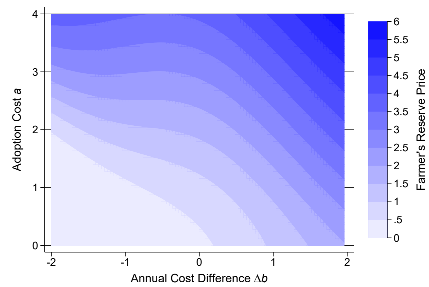


(a) The Effects of Varying Adoption Cost

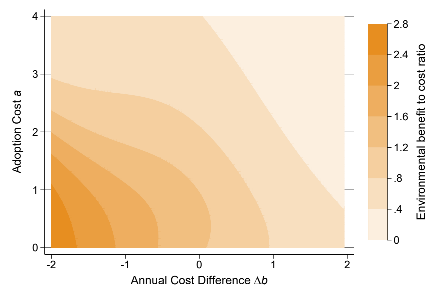


(b) The Effects of Varying Long-term Cost

Figure 7: Contract Costs and Net Benefits



(a) Farmer Reserve Prices for Contract



(b) Contract Efficiency at Reserve Price

from Equation 1 with the cover cropping choices in Equation 2, the farmer will accept a contract if

$$p \geq P(Additional)(a + \Delta b - E[\epsilon_1|\text{Equation 2}] - (1 - r)\Delta E[\pi_2]) \tag{6}$$

More additional farmers will tend to a have a higher minimum reserve price, since the contract will alter their expected profits only when they expect to change their behavior. Similarly, expected period 1 profit losses increase the farmer's reserve price. However, the needed payment is decreasing in $\Delta E[\pi_2]$, the farmer's expected change in long-term profits from having already paid the adoption cost. If a farmer thinks they will wish to cover crop in the future, they are more willing to pay the adoption cost today.

Graphing farmer reserve prices in Figure 7a, reserve prices move in the opposite direction of additionality. Higher adoption costs and higher annual costs increase the chance of additionality, but they drive the farmer's reserve cost upwards.

Given that additionality, cost, and long-term impact may not move together, who should the policymaker target? Assume that land provides some fixed environmental value e each year that a farm cover crops, and the planner discounts the environmental value at the interest rate r. If the policymaker knows the farmer's value of a_k and Δb_k, they can choose to offer farmers contracts with their reserve price p_k. The policymaker's expected value per dollar for offering a farmer this contract is therefore

$$Benefit_k/Cost_k = e\frac{Additional_k + (1-r)Longterm_k}{p_k} \tag{7}$$

Figure 7b plots the results assuming $e = 1$. In this model, it is actually more efficient for the policymaker to target the farmers with $\Delta b < 0$ for whom cover cropping is expected to be beneficial in the long run, since they both demand lower subsidies and have a more persistent effect when they are additional. The exact shape of the relationship between additionality and optimal targeting will vary across situations, as adoption costs, long-term costs, and error structures vary. However, it will rarely be the most cost-effective to target purely the "highest-additionality" populations, since they will require a high cost to implement a practice they would never find profitable on their own, and they are not likely to sustain the practice in the long term.

Comparing the farmers' reserve price of a contract also offers insight into who will select into a program. EQIP offers a price per acre p^{EQIP} for cover cropping that is fixed at the state level. Within a state, any eligible farmer whose reserve price is $\leq p^{EQIP}$ should therefore want to apply for EQIP. This means the pool of applicants will look like the sample in Figure 7a with $p <= p^{EQIP}$, represented by the lighter share of the graph. These applicants would disproportionately include farmers with low adoption prices and low annual costs, who are therefore particularly willing to adopt Figure 5 demonstrates that these farmers are also the ones with the highest chance of adopting a cover crop on their own and thus have lower short-term additionality.

This applicant selection effect explains why papers that compare successful applicants to nonapplicants may overestimate EQIP's additionality. The matching papers do control for a wide set of covariants, hoping to avoid omitting any variables that might determine a farmer's odds of adopting a practice on their own. However, a farmer's decision whether to apply to EQIP or not is a particularly strong signal of willingness to adopt, and one that is omitted from other analysis. A farmer who would never apply to EQIP also would have little or no interest in cover cropping without support, while the applicant pool will include a mix of always-adopters and sometimes-adopters. Since this paper limits analysis to the applicant pool, it limits comparisons to this more similar group.

3.3 Applications to Cover Cropping

Where does cover cropping actually fall in this diagram of adoption and annual costs? Scientists and economists have created a considerable literature on the adoption costs and ongoing costs and benefits of cover cropping. Annual costs and benefits are extremely heterogenous: as a farmer surveyed by the Conservation Technology Information Center, 2023 noted, "recipes... don't work in a living biological system." Both regional and farm-specific agroecological and economic conditions can greatly impact what cover cropping techniques are most appropriate, and can vary the costs and benefits of that optimal practice. In this section, I discuss the annual and adoption costs and benefits of cover cropping, then discuss what this means for optimal policy.

The annual cost of planting and killing the cover crop is highly heterogeneous based on a farmer's choice of cover crops and management methods. Nationally, total seed, planting, and termination costs may range from $15-$78 per acre (Myers et al., 2019). In Kansas alone, cover cropping requires between $42 to $119 per acre for seed, planting, fertilizer, application, and termination (Bergtold et al., 2019). Planting costs are more consistent, about $17.70 per acre in 2019, but seed and fertilizer costs are highly variable: from $24.50 per acre for crimson clover to $91.50 for densely planted and fertilized rye (ibid.).

Different choices of cover crop provide different benefits that may allow farmers to reduce their costs through a variety of methods. Cover crops can fix nitrogen, an important nutrient for crops, out of the air, allowing farmers to reduce fertilizer applications (Blanco-Canqui et al., 2012). 21% of corn growers surveyed by Conservation Technology Information Center, 2023 said that they reduced fertilizer costs by $20 or more per acre, though half reported spending the same on fertilizer after integrating cover cropping. Cover crops can also reduce herbicide costs in no-till systems, and can help with pest management (Snapp et al., 2005), though the ability of cover crops to help depends on what weed and pest pressure the field previously faced.

The changes that cover crops work on the soil can also lead to increased yield, though this effect is again highly variable. Cover crops can improve soil quality through improving moisture management, reducing soil compaction and erosion, and increasing soil organic matter (Bergtold et al., 2019). Together, these can help cash crops use nutrients more efficiently and produce larger harvests. In Corn Belt corn and soy systems, the areas that benefit the most from cover cropping may see yield increases of 15%, while the areas that are least suited for cover cropping may see a 5% decrease in yields (Deines et al., 2019). Cover crops can also help with water management, improving yields in drought years in regions of the Corn Belt(O'Connor, 2013), though cover crops in arid regions of the Great Plains may harm yields by depriving cash crops of needed moisture (Robinson and Nielsen, 2015).

Altogether, the annual profit impact of cover crops varies widely. While many farmers can implement cover crops profitably after an adjustment period, the magnitude of those expected returns for corn may range from $17 to $110 per acre after 5 years based on agroecological and economic characteristics including whether the farmers can graze livestock on the cover crops, if they practice no-till, or the year's weather (Myers et al., 2019). In Kansas, a cover crop may have a net return of $7 per year on irrigated land and a net cost of $28 per year on dryland systems (Bergtold et al., 2019), while more than half of South Dakota cover crop adopters believe that cover cropping has had little effect on the profitability of their operation (Wang et al., 2021).

This variability in the long-term optimal choice for cover cropping drives much of the adoption cost for cover cropping, which comes in the form of learning costs. Some farmers do need to pay physical adoption costs, such as no-till drills for planting or mechanical crimpers for killing the cover crop (Bergtold et al., 2019). However, farmers far more frequently cite the challenge of learning how to cover crop as the biggest barrier to adoption. When learning how to cover crop, a farmer risks making some costly mistakes, such as choosing the incorrect timing to kill the cover crop. Using herbicide for termination requires careful timing. Herbicide may persist in the soil and damage the cash crop if the farmer uses the herbicide too close to planting or uses too much for their particular soil and water conditions (Curran, 2016). However, waiting longer to kill the cover crop may give additional nitrogen benefits (Sainju and Singh, 2001) and help build the biomass needed to derive the full benefits of a cover crop (Morton et al., 2006). Farmers may also take several years to decide how to adjust their fertilizer usage in response to a cover crop. Cover crops can fix N in soils, reducing fertilizer needs, but the rate at which cover crops will make N available to cash crops can vary across locations and situations (Snapp et al., 2005).

Farmers' knowledge of cover cropping and their confidence in their ability to get these choices correct immediately may therefore be a substantial source of adoption cost heterogeneity. Even within a narrow geographic band of South Dakota, farmers who have not practiced cover cropping have widely dispersed beliefs about the impact of cover cropping on profitability (Wang et al., 2021). It may be possible to close some of this gap with education and supporting access to farmer networks, which farmers describe as key to getting the information they needed to adopt cover crops (Roesch-McNally et al., 2018). These farmer networks can provide the hyperlocal knowledge that farmers need, helping them learn from closely comparable farms.

Finally, it often takes farmers several years to realize the full benefits of cover croppng, even when they find the optimal way to implement cover cropping on their land. Cover cropping increases yields primarily through soil quality improvements, such as increased soil organic matter and improved moisture management. These changes accumulate slowly over several years of cover cropping, so many farmers will not see substantial benefits until the soil has improved for 3-5 years (Myers et al., 2019). Yield benefits for maize and soybeans increase slowly over the first several years since cover crop adoption, with yield benefits for fields that have used cover crops for a decade or more estimated to be 10 times as large as the effect in the first year (Deines et al., 2019)

Together, this tells us that farmers face some variable adoption costs to cover cropping, and their annual net costs of cover cropping range from the positive to the negative. With the high variation of annual net costs from profitability to prohibitive expense, participants could have any combination of short-term and long-term impact discussed above. Higher short-term additionality does not guarantee a greater long-term impact for a group, since there are farmers who would discontinue cover cropping without incentives.

In the empirical section, I test whether targeting on observables, such as farm size, crop type, or region, would allow policymakers to jointly maximize long-term and short-term impacts, or whether some groups show lower short-term but higher long-term impacts than others. While this data does not let me identify the underlying annual and adoption costs that farmers face, we can get an idea of how this variation matters.

3.4 Possible Extensions

This model is simplified to illustrate the roles of short-term and long-term costs of a practice in determining additionality and long-term impact, but it could be extended to accommodate a range of real-world considerations.

First, the model can be extended to more time periods. As the post-contract period grows longer, the long-term opportunities and costs of cover cropping will weigh more heavily for both farmers and the policymaker. As such, adoption costs will become less important to farmers than long-run profitability, and the policymaker will more strongly prefer the farmers with a high expected long-term effect over those with certain short-term additionality.

Also, changing risk structures could create new opportunities for efficient contracting. I currently assume a risk-neutral farmer, but this model could include a risk-adverse farmer. Risks could increase the short-term cost if farmers are uncertain about the adoption costs, or they could reduce long-term costs given that cover cropping can reduce damages from drought or irregular moisture patterns (Myers et al., 2019). The risk premium may alter farmers' reserve price for cover cropping, and it will do so differently across farmers if their actual or perceived levels of risk differ. Cover cropping is risk-reducing for farmers in some systems, such as Tennessee cotton (Boyer et al., 2018). If a practice increases risk, risk-neutral policymakers may be able to find more cost-efficient incentive solutions by offering insurance policies as well as fixed payments.

In addition, this model could include a transaction cost for contracting. High transaction costs would make the policymaker shift focus towards contracts with higher additionality and long-term impact, since it becomes expensive to pay the transaction costs for large numbers of cheap but lower-impact low additionality contracts. Introducing transaction costs would also mean that participants could be additional to the program but not to the practice, since some people for whom the practice is profitable would still not join the program unless the benefits are higher than their transaction costs. EQIP applicants report spending a modest 8.4 hours ex ante on planning and applications and 1.9 hours ex post on acceptance and compliance paperwork (McCann and Claassen, 2016). In this case, perceived transaction costs may be larger than the true transaction costs: 29% of nonapplicant producers surveyed about their reasons for not applying cited the application process as too complicated and time-consuming, and 31% gave the same concerns about documenting compliance (ibid).

4 Methodology

4.1 Regression Discontinuity Design

This paper instruments for receiving an EQIP contract with a regression discontinuity around the application score. The central regression specification is:

$$\begin{aligned} Y_{kgt} = \alpha_{gt} + \beta_1 Score_k + \beta_2 ScoreAcc_{kg} + \beta_3 ScoreAcc_{kg} * Score_k \\ + \beta_4 ScoreAcc_{kg} * During_{gt} + \beta_5 ScoreAcc_{kg} * After_{gt} + \\ \beta_6 During_{gt} + \beta_7 After_{gt} + \epsilon_k gt \end{aligned} \tag{8}$$

where Y_{kgt} is the outcome variable for field k in application pool g in year t and α_{gt} is a fixed effect for application pool g. $Score_k$ is the application score for field k relative to the group's threshold variable, and $ScoreAcc_k$ is an indicator variable that equals one if $Score_k$ is greater than or equal to the score acceptance threshold for that pool in that year. $During_{gt}$ and $After_{gt}$ are indicator variables that reference the year relative to the application year: $During_{gt}$ marks the three years after the application when successful applications would be under contract, and $After_{gt}$ indicates years four to nine after an application pool's contract term would end. β_4 and β_5 are the key variables of interest, since they estimate the differential effect of meeting the score threshold on applicant's behavior during the contract period and after the contract period respectively.

Scores are not a perfect predictor of treatment since some participants accepted based on scores later drop out of their contracts and some participants are accepted in later years. Therefore, I use the fuzzy regression discontinuity estimator of treatment effects. For each variable of interest Y, I derive the short term effect of contracting as

$$TE^Y = \frac{\hat{\beta}_4^Y}{\hat{\beta}_2^P + \hat{\beta}_4^P} \tag{9}$$

where $\hat{\beta}_4^Y$ is the $\hat{\beta}_4$ estimated using Equation 8 with variable Y as the dependent variable, and $\hat{\beta}_2^P + \hat{\beta}_4^P$ are the coefficients estimated using Equation 8 with the probability of receiving an EQIP contract as the dependent variable. I similarly derive the long-term effect as $TE^Y = \frac{\hat{\beta}_5^Y}{\hat{\beta}_2^P + \hat{\beta}_5^P}$.

4.2 Identifying the Acceptance Threshold

To use this technique successfully first requires identifying what the threshold score for acceptance is within each funding pool and year. While accurately tracking the score of each individual application is one of the ProTract dataset's key administrative tasks, it does not explicitly track score cutoffs. Using ProTracts' annual snapshot of accepted and rejected applications, I estimate the threshold for each score through a two-step process. First, I identify pools using the group listed in ProTracts and application batch dates from USDA listings. Second, I find the lowest score of an application accepted in the first reporting year from that batch and use that as the cutoff score.

The first task is identifying the pools. In the EQIP funding process, the state-level USDA office first screens applicants for eligibility, then sorts applications into bins of its choosing. They often define these pools by geographic area within the state, by crop or animal production, or by resource concern such as water quality or wildlife habitat. Within ProTracts, these are listed by fund code. The fund code is reported for 99.8% of applications that have completed the scoring process, and applications without a fund code are omitted from the sample. The median state has 50 pools in a given year.

The USDA then evaluates these pools in batches. All applications received before a certain cutoff date are evaluated for funding at once. Applications received after that date will be rolled into the next evaluation and funding group. State USDA offices may choose their own evaluation dates, and they may perform these evaluations one to four times per year (USDA NRCS, 2018).

To track these dates, I cross-reference the ProTracts signup date of the application with the USDA's listed EQIP deadlines for a state. The signup date is the date at which the USDA receives a complete application that is ready for scoring and evaluation. The USDA listed EQIP deadlines come from a centralized page maintained from 2022 to 2024 that linked producers to their state's filing deadlines and application websites. Using the WayBack machine, I recorded all application dates from those years. Older application dates are not systematically recorded. Application dates for a state wavered somewhat over time, but stayed relatively constant: 78% were within the same month, allowing the date to vary to keep the day of the week constant. To accommodate these variations, I assume an actual batch cutoff three weeks after the later date within a month. Application levels decrease immediately after a cutoff, so this method is unlikely to misclassify many applications that belong in the next pool. Also, some offices may have changed the number of cutoff dates within a year over time. Between 2022 and 2024, 15 states had a different number of listed batch dates within at least one year. In those cases I use the highest listed number of batch dates since the Wayback Machine may have failed to capture some of the repeat dates. Since this may split some batches into multiple batches for analysis, it may weaken the power of my analysis, but should not introduce bias.

Within pools, applications are funded in order of scores until the category has allocated all available funds. Pools therefore vary widely by the acceptance rate. 11% of applications in included years are in pools where all applications that meet the minimum eligibility requirements are funded. These fully funded pools are generally smaller, receiving a mean of 2.8 applications per fully funded pool compared to 26.1 per competitive pool. I omit the fully funded pools from my regression discontinuity analysis because they do not have a score discontinuity. Applications that cannot be funded in a year are deferred, and are eligible to subsequently resubmit the same application in another year.

4.3 Threats to Identification

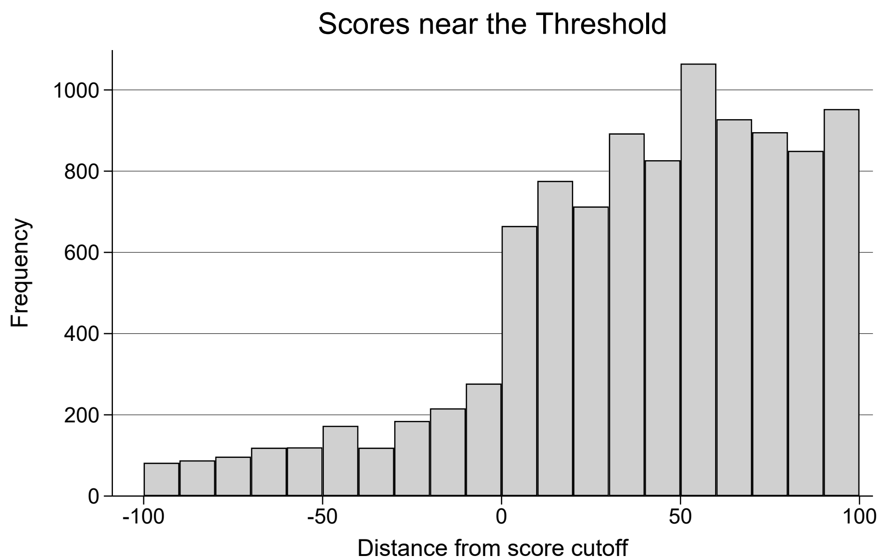
In this section I discuss two key threats to identification: manipulation of the score around the threshold, and differential nonrandom data loss. First, this identification relies on the assumption that whether a farmer's application score falls just above or below the threshold is essentially random. The barely successful applicants must not be systematically different from the barely unsuccessful applicants. This can happen if some applicants are aware of their proximity to the threshold and are able to alter their applications to push them over the edge.

Overall, this kind of precision manipulation is highly unlikely in this setting. Applicants need two levers to take advantage of the threshold: they must have some power to manipulate their scores, and they must have an idea of their proximity to the cutoff. EQIP does give producers the first since applicants will receive different scores based partially on the suite of practices they choose to offer. However, anticipating the score cutoff would be quite difficult. Since the state USDA funds applications in a pool until all the pool's allocated funds are committed, the cutoff score depends on both who applies to a pool in a given year and on how much funding the state allocates to the pool. Given fluctuations in the number of applications and funding, acceptance scores can swing substantially across years. Nationwide acceptance rates varied from 15 to 67% between 2000 and 2011, swinging back and forth based on EQIP funding and on application numbers (Stubbs, 2011). In addition, the exact formula for the application score is not publicized. In conversation with USDA employees and with other producers in their area, an applicant might glean a rough idea of whether their pool will be particularly competitive in a given year. However, even those USDA employees would find it nearly impossible to predict the exact acceptance score of a competitive pool. The graph in Figure 8 of matched scores near the discontinuity bears this out. While there is differential missingness of data across the discontinuity, there is no particular bunching of scores just above or missing mass just below.

The difference in counts of successful and unsuccessful applications in my data is instead due to differential missingness. As discussed in the data section, there are two ways that applications may drop out of my sample. The first is that rejected contracts and deferred contracts that the applicant does not wish to resubmit are purged from the ProTracts system once annually. To manage this problem, I remove some years where the data purge and data pull may have happened in close proximity. The second channel is that some data is lost in the match from ProTracts to CARD, and unsuccessful applications have poorer match rates. While 79% of initially successful ProTracts applications in my target states have numeric geographic data, only 27% of deferred applications have this data. Ultimately, 42% of successful applications and 15% of unsuccessful applications in ProTracts can be matched to CARD.

I also check for the frequency of repeat applications and find that while many applicants will resubmit their application until accepted, submitting a new repeat application is relatively uncommon. I find that only 21% of deferred

Figure 8: Scores Near the Threshold



applicants in ProTracts are later accepted. However, since never-accepted applications are less likely to have matchable CLU data, 85% of CARD-matched deferred applicants used in my sample are later accepted. I also find that only 5% of farm fields appear in more than one contract or application over time, suggesting that few farmers who are rejected once consider it worth their time to apply again.

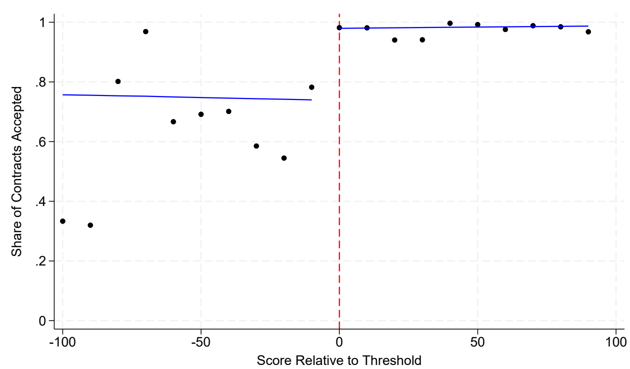
5 Results

5.1 Difference-in-difference results

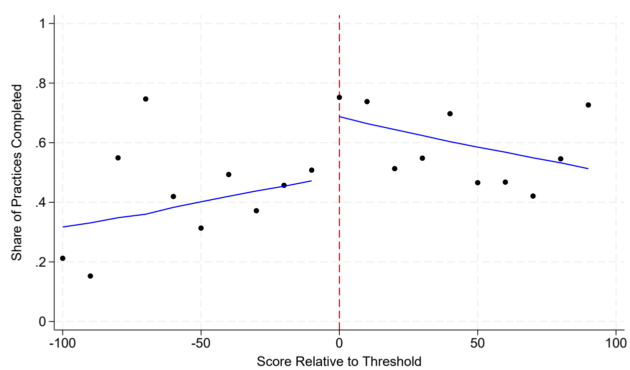
First, I find that having a score above the acceptance threshold for the initial application round increases the probability of having the contract ever accepted and the probability of completing a contracted practice by 20%. Figure 9 shows the discontinuity. Almost all applications that are deemed eligible accept the contract, as we would expect given that a farmer must put effort into producing their bid. 78% of applicants just below the threshold ultimately end up receiving a contract in subsequent years as their initially deferred application proves successful in another year's less competitive application pool. This probability of a later successful application stays quite constant across the hundred-point bandwidth, suggesting there is not much substantial variation in applicant traits across this range. Contract completion by 2020 takes a similar path to contract acceptance, since only 14.5% of farmers with cover cropping contracts do

Figure 9: Discontinuity in Contract Acceptance and Completion

(a) Contract Acceptance



(b) Contract Completion



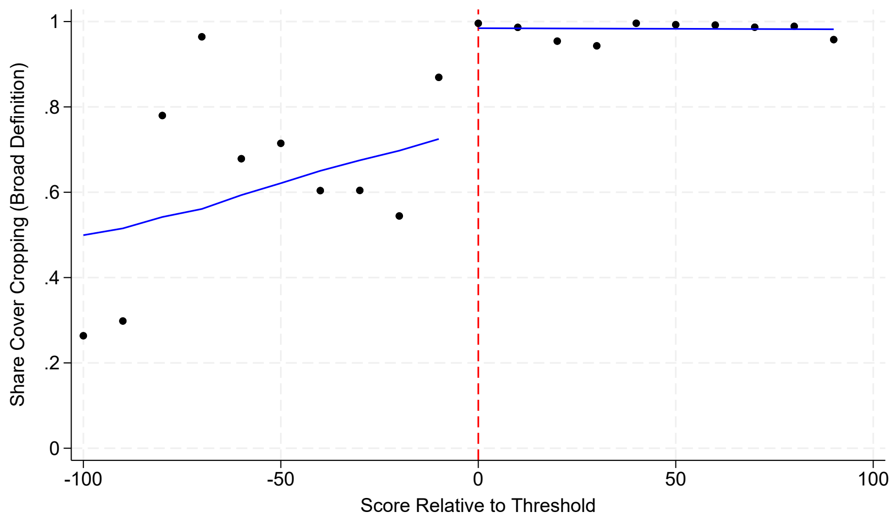
not complete their practices (Wallander et al., 2019). The lower level of contract completion overall reflects that many contracts in this dataset had not yet reached the end of their planned duration by 2020.

Figure 10 shows that cover cropping also increases at the discontinuity, even before controlling for pool fixed effects as in the full regression. By the broad definition, cover cropping increases by 25% at the discontinuity during the contract period. The post effects are difficult to detect without the appropriate controls, but do show a slight increase in post-contract cover cropping.

The results of the full regression discontinuity, shown in Table 2, estimate that being above the score threshold increases the chance of contract acceptance for the during-contract group by 47% and increases during-contract cover cropping by 46%. These effects are combined to estimate the contract effect after and during contract at the bottom of Table 2. The coefficients are calculated according to Equation 9, using the Table 2 Column 3 results for $\hat{\beta}^P$. I estimate standard errors for these effects using the delta method. The resulting analysis

Figure 10: Discontinuity in Short- and Long-Term Cover Cropping

(a) Cover Cropping During Contract Period



(b) Cover Cropping After Contract Period

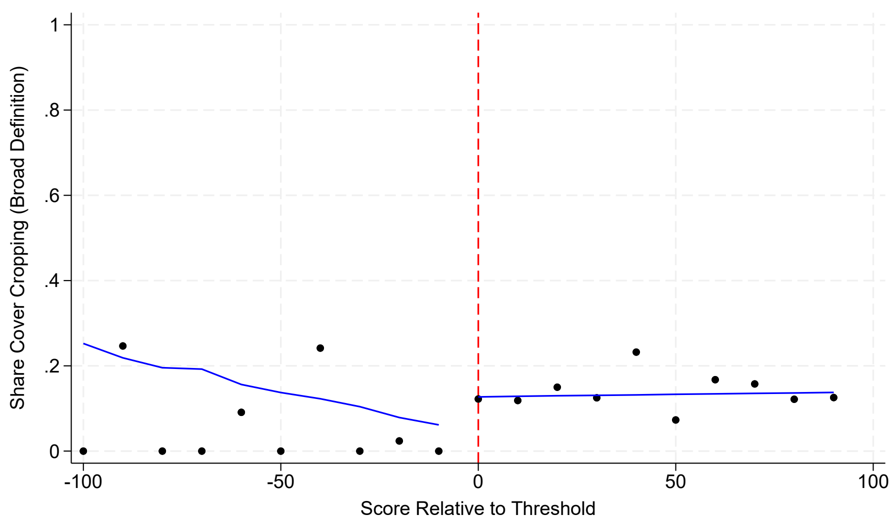


Table 2: Regression Discontinuity Results

VARIABLES	(1) Cover Cropping (CARD/EQIP Max)	(2) Cover Cropping (CARD only)	(3) Contract Accepted	(4) Practice Certified
Application Score	0.00109***	0.000512***	0.00317***	0.000716***
	(0.000119)	(0.000136)	(0.000110)	(0.000120)
Score # Score Above Threshold	-0.00157***	-0.000999***	-0.00298***	-0.000677***
	(0.000120)	(0.000138)	(0.000111)	(0.000121)
During Contract	0.459***	-0.0871***	-0.374***	-0.771***
	(0.0131)	(0.0148)	(0.0453)	(0.0575)
After Contract	0.111***	-0.0557***	0.764***	1.450***
	(0.0141)	(0.0132)	(0.0336)	(0.0432)
Score Above Threshold	-0.0351***	-0.0350***	-0.00200	0.00891*
	(0.00507)	(0.00589)	(0.00380)	(0.00500)
Score Above Threshold # During Contract	0.465***	0.101***	0.475***	0.933***
	(0.0128)	(0.0146)	(0.0148)	(0.0184)
Score Above Threshold # After Contract	0.0203**	0.0540***	0.00534	-0.0422***
	(0.00823)	(0.00945)	(0.00621)	(0.00799)
Pool Fixed Effects	Yes	Yes	Yes	Yes
Contract Effect During Contract	0.968***	0.210***		
	(0.0403)	(0.0265)		
Contract Effect After Contract	4.135	10.42		
	(5.331)	(14.05)		
Observations	630,917	614,992	711,903	718,341
R^2	0.695	0.256	0.488	0.903
Number of id	114,312	114,274	113,388	114,312

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

finds that receiving an EQIP contract increases during-contract cover cropping by 96% during the contract and continues to increase cover cropping after. This high level of short-term additionality is consistent with estimates from elsewhere in the literature (Claassen et al., 2018, Mezzatesta et al., 2013, Fleming et al., 2018).

The persistence of change is difficult to detect in the current sample, but potentially quite large. Since the bulk of application pools with comprehensive data on unsuccessful contracts were made between 2014 and 2017 and the cover-cropping panel tracks fields from 2013 to 2019, the post-contract acceptance discontinuity is smaller and based on data with higher missingness. Accordingly, the contract effect after contract as estimated with Equation 9 and shown in Table 2 has a wide confidence interval, with a coefficient estimate of 4.135 and a standard error of 5.331. As further research tracks the outcomes of the 2014 to 2017 application groups, more precise estimates of the long term effect should become possible.

5.2 Effects on Subgroups

This section explores the differential effects on subgroups by region and by acreage under contract. Both tracked in the application database, these variables are used for decisions on targeting funding and awarding contracts, so understanding where EQIP cover cropping is particularly effective and ineffective is valuable for targeting. This section also tests the relationship between duration and addtionality across subgroups. As discussed in the model section, additionality could and duration could either covary or oppose one another depending on the distribution of adoption and long-term costs. In this context, I find that subgroups with higher additionality tend to have lower long-term effects, so targeting exclusively on additionality could lead to poorer long-term outcomes.

First I calculate the treatment effect by the acreage included in a cover cropping contract application. I divide contracts into three acreage groups with approximately equal numbers of applications: small contracts with less than 100 acres, large contracts with more than 1000 acres, and the medium contracts in between. I then regress with interactions for size, and calculate each group's treatment coefficient using Equation 9. The resulting treatment effects are plotted in Figure 11a.

This analysis finds that short-term additionality is increasing but long-term impact is decreasing in contract size. Small contracts covering less than 100 acres have an estimated additionality of 20%, while the largest contracts have 60% estimated additionality. Long-term effect estimates have large confidence intervals, but trend downwards with size: the small contracts have an estimated treatment effect of 1.5, and large contracts have an estimated treatment effect of .6. The 95% confidence intervals for all groups overlap. However, the confidence intervals do show that additionality is either increasing or approximately constant with acreage, and long-term effects are either constant or decreasing with acreage.

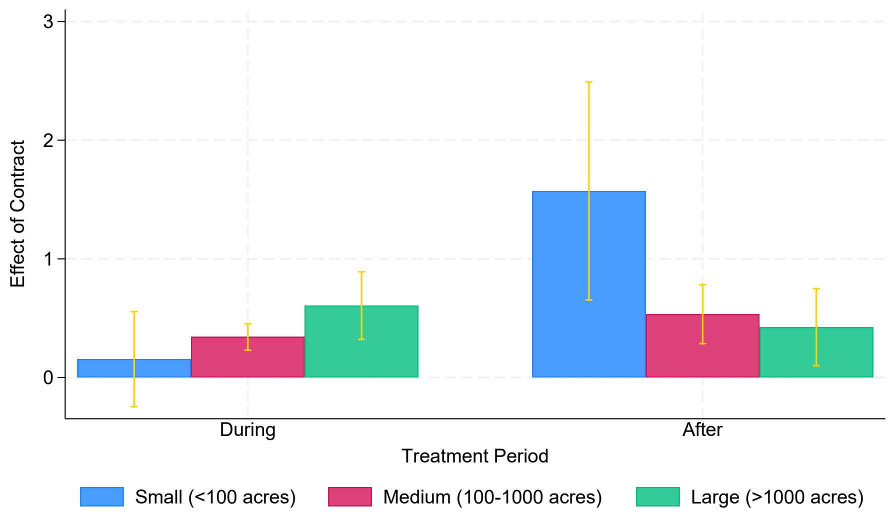
I also analyze heterogeneity by USDA production region, with results in Figure 11b. While these estimates are often noisy, most regions do not show substantial effects in the short or the long term, including the key Corn Belt region of substantial interest to many private sector cover crop programs. The key exceptions are Appalachia and the Northern Plains. Contracts in Appalachia show the lowest additionality and highest long-term effect of any region, and Northern Plains contracts conversely have the highest additionality and second smallest long-term impact estimated.

Both sets of heterogeneous treatment effects share a trend: additionality and long-term impact of subpopulations pull in opposite directions. To better visualize this, Figure 12 plots long-term and short-term effects of contracts together, with treatment effects winsorized to a maximum value of 1 and minimum value of 1 for clearer visualization. For each set of effects, point estimates slope downward across the graph, indicating a tradeoff between additionality and long-term impact.

This paper's model predicts that this will occur when subgroups primarily vary by the long-term cost of cover cropping rather than the adoption cost. When cover cropping is profitable in the long run, we expect low additionality and higher long-term effects. When it is unprofitable, we expect substantial additionality but high rates of discontinuation after incentives end. This makes improving program targeting difficult. If the NRCS used this paper's additionality estimates to target high-additionality groups like the Northern Plains and

Figure 11: Treatment Effects by Subgroups

(a) Differential Effects by Contract Acreage



(b) Treatment Effects by Region

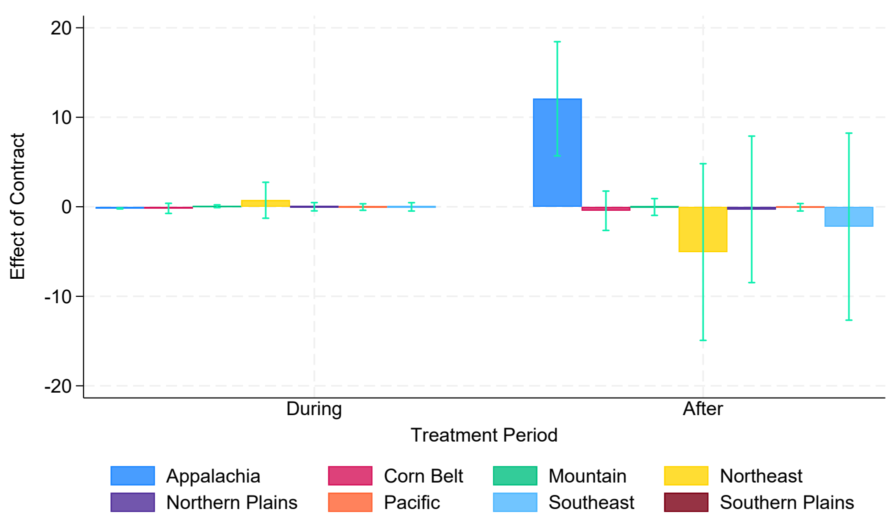
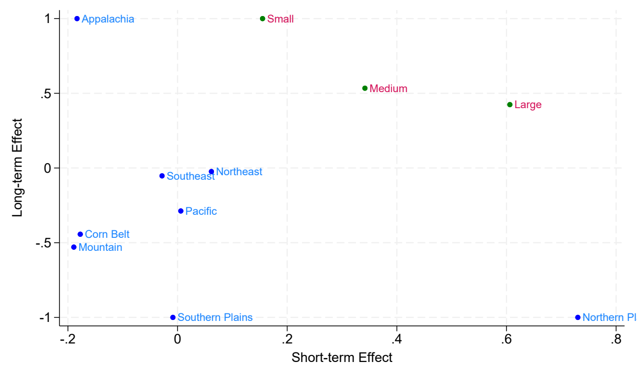


Figure 12: Long-term and Short-term Treatment Effects on Subgroups



Effect size winsorized at [-1, 1]

large contracts, this would shift funding away from groups where the effect of EQIP will persist more strongly in the long run.

6 Conclusion

Like many environmentally beneficial practices, cover cropping requires effort both to adopt and to maintain. The perceived size of the adoption costs and the the long-run costs or benefits can determine whether a farmer will adopt the practice on their own, whether they'll apply for programs like EQIP that offer transition funding, and whether they'll continue the practice after incentives end. This paper finds that the EQIP cover cropping program participants are largely additional, with program acceptance increasing the chance of cover cropping by 95%. The translation into long-term practice change is uncertain.

However, subgroup effects suggest that long-term and short-term effects cannot easily be jointly targeted for cover cropping. As this paper's model explains, long-term effects of short-term incentive programs depend on both the practice's additionality and on farmers' willingness to persist with it after incentives end. Farmers for whom cover cropping would be somewhat profitable in the long run are more likely to adopt on their own, but they are also more likely to keep using the practice. Subgroups such as small farms and those in Appalachia seem to fall into that category where low short-term effects are paired with higher long-term effects. Conversely, groups for whom the practice is less profitable to sustain will be more additional but have a lower long-term impact, which fits the results for larger parcels and the Northern Plains region. Adoption costs may be similar across these subpopulations with some random variation, but these results are not consistent with a strong positive or negative correlation between adoption costs and long-term costs.

This indicates that in cover cropping, targeting exclusively based on additionality may lead to long-term losses. In this context and others, evaluators measure additionality more frequently than long-term impact, and policymakers may be tempted to focus on improving additionality through adding new eligibility restrictions. That instinct could increase a program's impact if participants mostly vary by adoption costs. However, if that variation in additionality is due to long-term costs, policymakers risk cutting into their program's long-term impact. Cover cropping is known to have highly variable long-term benefits, and the subgroup results in this paper suggest that the variation in long-term benefits dominates any effect of variation in adoption costs.

These findings also highlight potential challenges for voluntary carbon credit markets for cover cropping. Given the mixed additionality and persistence found among subgroups in this study, a carbon crediting program would struggle to guarantee both that the carbon they store is additional and that it would persist. To manage the additionality problem, the credit program might choose to discount credits based on the estimated overall level of additionality. To deal with the rerelease problem, the credit market might design some program to replace credits after carbon is released or switch to a credit-year system, which sets a ton of temporary storage as worth a fraction of a permanent ton emitted (Brandão and Levasseur, 2011; Fearnside et al., 2000). Any of these solutions will decrease the size of the market payment available to farmers and thus may limit the program's ability to create large-scale change.

Short-term payment programs like EQIP can avoid some of these difficulties. Mismeasuring the additionality and long-term benefits of government payments may lead to inefficient uses of funds, but it will not lead to excess greenhouse gas release as nonadditional private market credits might. In addition, government incentive programs can take into account the full range of externalities provided by a practice: cover cropping incentives have significantly improved water quality in the Chesapeake Bay (Fleming et al., 2018), and the first cover cropping incentives were designed only in response to concerns around soil and water quality (Turner et al., 2014).

In addition, policymakers can use this framework of short-term and long-term costs to design the structure of repeat payment programs. EQIP's one-time contract structure can provide all needed support for changes that need adoption costs but face few if any long-term costs, such as building water management structures. However, depending on the farm, some carbon-storing practices like cover cropping and reduced tillage may produce long-term environmental benefits but not enough financial benefits for the producer to continue them on their own. In those cases, repeat contracts with smaller payments that cover these ongoing costs could have substantial additionality. This highlights a role for programs like the Conservation Stewardship Program (CSP), a USDA program that pays past conservation practice adopters to enhance or add new conservation practices while sustaining previous ones.

This paper also illustrates the need for more work in this area that controls for the application decision and that follows practices over longer periods of time. There have historically been few data sources that reliably track farmers over time, and connecting farmers to past program participation has typically relied on imperfect recall questions. Modern satellite imagery databases may make tracking practices in individual fields over time more achievable. The ProTracts database used in this project was designed primarily to track successful applications and not unsuccessful ones, which led to the differential missingness of unsuccessful applications in this paper's sample. To improve the precision of the long-term effects estimated here, I will continue to incorporate more years of outcomes as they become available. Future programs should put care into tracking unsuccessful applicants, since they are a subgroup that are likely to be more similar in terms of unobservables than any other group. In addition, they are particularly relevant when exploring the likely effects of marginal increases or decreases in program funding.

In future work, researchers can also explore how a range of nature-based solutions fit into this framework of adoption and long-term costs. Nature-based solutions could provide up to 30% of the the emissions reductions needed to meet global goals (Miles et al., 2021). They include a wide range of practice changes, including improved forestry management, reduced tillage and other agricultural changes, regenerative rangeland management, agroforestry, and shifts in nutrient management. Achieving the full potential of these changes will require tailoring incentives to a wide variety of economic and biological contexts. The adoption cost/long-term cost framework of this paper can provide a starting point for that work, ideally through estimating average adoption and long-term costs and through how much they vary within and between populations.

References

Arbuckle, J. G., & Roesch-McNally, G. (2015). Cover crop adoption in iowa: The role of perceived practice characteristics [Publisher: Soil and Water Conservation Society Section: Research Section]. *Journal of Soil and Water Conservation*, *70*(6), 418–429. https://doi.org/10.2489/jswc.70.6.418

Barnes, J. C., Sketch, M., Gramza, A. R., Sorice, M. G., Iovanna, R., & Dayer, A. A. (2020). Land use decisions after the conservation reserve program: Re-enrollment, reversion, and persistence in the southern great plains [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/csp2.254]. *Conservation Science and Practice*, *2*(9), e254. https://doi.org/10.1111/csp2.254

Baumgart-Getz, A., Prokopy, L. S., & Floress, K. (2012). Why farmers adopt best management practice in the united states: A meta-analysis of the adoption literature. *Journal of Environmental Management*, *96*(1), 17–25. https://doi.org/10.1016/j.jenvman.2011.10.006

Bergtold, J. S., Ramsey, S., Maddy, L., & Williams, J. R. (2019). A review of economic considerations for cover crops as a conservation practice. *Renewable Agriculture and Food Systems*, *34*(1), 62–76. https://doi.org/10.1017/S1742170517000278

Blanco-Canqui, H., Claassen, M. M., & Presley, D. R. (2012). Summer cover crops fix nitrogen, increase crop yield, and improve soil–crop relationships [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.2134/agronj2011.0240]. *Agronomy Journal*, *104*(1), 137–147. https://doi.org/10.2134/agronj2011.0240

Boyer, C. N., Lambert, D. M., Larson, J. A., & Tyler, D. D. (2018). Investment analysis of cover crop and no-tillage systems on tennessee cotton [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.2134/agronj2017.08.0431]. *Agronomy Journal*, *110*(1), 331–338. https://doi.org/10.2134/agronj2017.08.0431

Brandão, M., & Levasseur, A. (2011, January 1). *Assessing temporary carbon storage in life cycle assessment and carbon footprinting: Outcomes of an expert workshop.*

Claassen, R., Duquette, E. N., & Smith, D. J. (2018). Additionality in u.s. agricultural conservation programs [Publisher: University of Wisconsin Press]. *Land Economics*, *94*(1), 19–35. https://doi.org/10.3368/le.94.1.19

Conservation Technology Information Center. (2023, August). *National cover crop survey report 2022-2023.*

Curran, W. S. (2016). Persistence of herbicides in soil [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.2134/ 49-0504]. *Crops & Soils*, *49*(5), 16–21. https://doi.org/10.2134/cs2016-49-0504

Deines, J. M., Wang, S., & Lobell, D. B. (2019). Satellites reveal a small positive yield effect from conservation tillage across the US corn belt [Publisher: IOP Publishing]. *Environmental Research Letters*, *14*(12), 124038. https://doi.org/10.1088/1748-9326/ab503b

Drechsler, M., Johst, K., & Wätzold, F. (2017). The cost-effective length of contracts for payments to compensate land owners for biodiversity conservation measures. *Biological Conservation*, *207*, 72–79. https://doi.org/10.1016/j.biocon.2017.01.014

Dynarski, K. A., Bossio, D. A., & Scow, K. M. (2020). Dynamic stability of soil carbon: Reassessing the "permanence" of soil carbon sequestration [Publisher: Frontiers]. *Frontiers in Environmental Science*, *8*. https://doi.org/10.3389/fenvs.2020.514701

Environmental Working Group. (2023). EWG conservation database. https://conservation.ewg.org/index.php

Fearnside, P. M., Lashof, D. A., & Moura-Costa, P. (2000). Accounting for time in mitigating global warming through land-use change and forestry. *Mitigation and Adaptation Strategies for Global Change*, *5*(3), 239–270. https://doi.org/10.1023/A:1009625122628

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. https://doi.org/10.1016/j.jeem.2018.08.007

Gonzalez-Ramirez, J., Kling, C., & Arbuckle, J. G. (2015). *Cost-share effectiveness in the adoption of cover crops in iowa* (2015 AAEA & WAEA Joint

Annual Meeting, July 26-28, San Francisco, California No. 205876). Agricultural and Applied Economics Association. Retrieved August 6, 2024, from https://econpapers.repec.org/paper/agsaaea15/205876.htm

Happ, M. (2021, September 9). *Closed out: How u.s. farmers are denied access to conservation programs*. Retrieved September 27, 2024, from https://www.iatp.org/documents/closed-out-how-us-farmers-are-denied-access-conservation-programs

Kladivko, E. J., Kaspar, T. C., Jaynes, D. B., Malone, R. W., Singer, J., Morin, X. K., & Searchinger, T. (2014). Cover crops in the upper midwestern united states: Potential adoption and reduction of nitrate leaching in the mississippi river basin [Publisher: Soil and Water Conservation Society Section: Research Section]. *Journal of Soil and Water Conservation*, *69*(4), 279–291. https://doi.org/10.2489/jswc.69.4.279

Laloy, E., & Bielders, C. L. (2010). Effect of intercropping period management on runoff and erosion in a maize cropping system [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.21 *Journal of Environmental Quality*, *39*(3), 1001–1008. https://doi.org/10.2134/jeq2009.0239

Lichtenberg, E., Wang, H., & Newburn, D. (2018, June 20). *Uptake and additionality in a green payment program: A panel data study of the maryland cover crop program* (No. 274455) (Publication Title: 2018 Annual Meeting, August 5-7, Washington, D.C.). Agricultural and Applied Economics Association. Retrieved August 5, 2021, from https://ideas.repec.org/p/ags/aaea18/274455.html

Lötjönen, S., Kulovesi, K., Lång, K., & Ollikainen, M. (2024). Offset ratios and temporary contract designs for climate integrity in carbon farming [Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/17583004.2024.2329593]. *Carbon Management*, *15*(1), 2329593. https://doi.org/10.1080/17583004.2024.2329593

McCann, L., & Claassen, R. (2016). Farmer transaction costs of participating in federal conservation programs: Magnitudes and determinants [Publisher: University of Wisconsin Press Section: Articles]. *Land Economics*, *92*(2), 256–272. https://doi.org/10.3368/le.92.2.256

Mezzatesta, M., Newburn, D., & Woodward, R. (2013). Additionality and the adoption of farm conservation practices. *Land Economics*, *89*. https://doi.org/10.3368/le.89.4.722

Miles, L., Agra, R., Sengupta, S., Vidal, A., & Dickson, B. (2021, November 4). *Nature-based solutions for climate change mitigation*. UN Environmental Programme. Retrieved November 2, 2024, from https://portals.iucn.org/library/node/49781

Morton, T., Bergtold, J., & Price, A. (2006). The economics of cover crop biomass for corn and cotton.

Murray, B. C., Sohngen, B., & Ross, M. T. (2006). Economic consequences of consideration of permanence, leakage and additionality for soil carbon sequestration projects [Last Modified: 2018-06-08T10:25-04:00 Publisher: Kluwer Academic Publishers]. *Climatitic Change*, *2007*(80), 127–143. Retrieved January 22, 2024, from https://nicholasinstitute.duke.edu/

environment / publications / naturalresources / economic - consequences - of - consideration - of - permanence - leakage - and - additionality - for - soil - carbon-sequestration-projects-1

Myers, R., Weber, A., & Tellatin. (2019, June). *Cover crop economics*. SARE. Retrieved January 17, 2024, from https://www.sare.org/resources/cover-crop-economics/

NRCS. (2024). *Financial assistance program dashboard* [Farmers.gov]. Retrieved December 18, 2024, from https://www.farmers.gov/data/financial-assistance-overview

O'Connor, C. (2013). Soil matters: How the federal crop insurance program should be reformed to encourage low-risk farming methods with high-reward environmental outcomes [Number: 156789 Publisher: Agricultural and Applied Economics Association]. *2013 AAEA: Crop Insurance and the Farm Bill Symposium*. Retrieved October 15, 2024, from https://ideas.repec.org//p/ags/aaeaci/156789.html

Oldfield, E. E., Eagle, A. J., Rubin, R. L., Rudek, J., Sanderman, J., & Gordon, D. R. (2022). Crediting agricultural soil carbon sequestration [Publisher: American Association for the Advancement of Science]. *Science*, *375*(6586), 1222–1225. https://doi.org/10.1126/science.abl7991

Pannell, D. J., & Claassen, R. (2020). The roles of adoption and behavior change in agricultural policy [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/aepp.13009]. *Applied Economic Perspectives and Policy*, *42*(1), 31–41. https://doi.org/10.1002/aepp.13009

Park, B., Rejesus, R. M., Aglasan, S., Che, Y., Hagen, S. C., & Salas, W. (2023). Payments from agricultural conservation programs and cover crop adoption [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/aepp.13248]. *Applied Economic Perspectives and Policy*, *45*(2), 984–1007. https://doi.org/10.1002/aepp.13248

Poeplau, C., & Don, A. (2015). Carbon sequestration in agricultural soils via cultivation of cover crops – a meta-analysis. *Agriculture, Ecosystems & Environment*, *200*, 33–41. https://doi.org/10.1016/j.agee.2014.10.024

Pratt, B., Paul, L., Bowman, M., Ferraro, P., Messer, K., & Gao, J. (2023). Longitudinal measurement of cover crop use and persistence.

Reimer, A. P., Weinkauf, D. K., & Prokopy, L. S. (2012). The influence of perceptions of practice characteristics: An examination of agricultural best management practice adoption in two indiana watersheds. *Journal of Rural Studies*, *28*(1), 118–128. https://doi.org/10.1016/j.jrurstud.2011.09.005

Robinson, C., & Nielsen, D. (2015). The water conundrum of planting cover crops in the great plains: When is an inch not an inch? [_eprint: https://onlinelibrary.wiley.com/doi/pdf/ 48-1-7]. *Crops & Soils*, *48*(1), 24–31. https://doi.org/10.2134/cs2015-48-1-7

Roesch-McNally, G. E., Basche, A. D., Arbuckle, J. G., Tyndall, J. C., Miguez, F. E., Bowman, T., & Clay, R. (2018). The trouble with cover crops: Farmers' experiences with overcoming barriers to adoption [Publisher:

Cambridge University Press]. *Renewable Agriculture and Food Systems*, *33*(4), 322–333. https://doi.org/10.1017/S1742170517000096

Rosenberg, A. B., Pratt, B., & Arnold, D. (2022). Land use impacts of the conservation reserve program: An analysis of rejected CRP offers. https://doi.org/10.22004/ag.econ.316533

Rosenberg, A. B., Pratt, B., & Szmurlo, D. (2024). Impacts of an increase in federal assistance for cover cropping: Evidence from the environmental quality incentives program [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ajae.12502]. *American Journal of Agricultural Economics*, *n/a*. https://doi.org/10.1111/ajae.12502

Sainju, U. M., & Singh, B. P. (2001). Tillage, cover crop, and kill-planting date effects on corn yield and soil nitrogen [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.2134/agronj2 *Agronomy Journal*, *93*(4), 878–886. https://doi.org/10.2134/agronj2001.934878x

Sawadgo, W., & Plastina, A. (2021). Do cost-share programs increase cover crop use? empirical evidence from iowa. *Renewable Agriculture and Food Systems*, *36*(6), 527–535. https://doi.org/10.1017/S1742170521000132

Schipanski, M. E., Barbercheck, M., Douglas, M. R., Finney, D. M., Haider, K., Kaye, J. P., Kemanian, A. R., Mortensen, D. A., Ryan, M. R., Tooker, J., & White, C. (2014). A framework for evaluating ecosystem services provided by cover crops in agroecosystems. *Agricultural Systems*, *125*, 12–22. https://doi.org/10.1016/j.agsy.2013.11.004

Snapp, S. S., Swinton, S. M., Labarta, R., & Mutch, D. (2005). Evaluating cover crops for benefits, costs and performance within cropping system niches [Num Pages: 11 Place: Madison, United States Publisher: American Society of Agronomy Section: REVIEW AND INTERPRETATION]. *Agronomy Journal*, *97*(1), 322–332. Retrieved October 15, 2024, from https://www.proquest.com/docview/194507436/citation/A73C0A2EC94F4CBAPQ/1

Stubbs, M. (2011, May 9). *Environmental quality incentives program (EQIP): Status and issues* (R40197). Congressional Research Service.

Turner, B., Wuellner, M., Nichols, T., & Gates, R. (2014). Dueling land ethics: Uncovering agricultural stakeholder mental models to better understand recent land use conversion. *Journal of Agricultural and Environmental Ethics*, *27*(5), 831–856. https://openprairie.sdstate.edu/nrm_pubs/88

USDA NRCS. (2018, April). *Title 440-conservation programs manual, part 512 - conservation program contracting* (No. 440-512-M). USDA NRCS.

Wallander, S., Bowman, M., Beeson, P., & Claassen, R. (2017, December 1). *Farmers and habits: The challenge of identifying the sources of persistence in tillage decisions* (2018 Allied Social Sciences Association (ASSA) Annual Meeting, January 5-7, 2018, Philadelphia, Pennsylvania No. 266307). Agricultural and Applied Economics Association. Retrieved January 22, 2024, from https://econpapers.repec.org/paper/agsassa18/266307.htm

Wallander, S., Claasen, R., Hill, A., & Fooks, J. (2019, March). *Working lands conservation contract modifications: Patterns in dropped practices* (Economic Research Report No. 262). USDA.

Wang, T., Xu, Z., Kolady, D., Ulrich-Schad, J. D., & Clay, D. (2021). Cover crops usage in south dakota: Farmer perceived profitability and future adoption decisions. *Journal of Agricultural and Resource Economics*, *46*(2), 287–307. Retrieved January 9, 2024, from https://jareonline.org/articles/cover-crops-usage-in-south-dakota-farmer-perceived-profitability-and-future-adoption-decisions/

Wittwer, R. A., Dorn, B., Jossi, W., & van der Heijden, M. G. A. (2017). Cover crops support ecological intensification of arable cropping systems [Publisher: Nature Publishing Group]. *Scientific Reports*, *7*(1), 41911. https://doi.org/10.1038/srep41911