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Selection and the Additionality of Incentives for Environmental Conservation

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Abstract

Agriculture has large impacts on environmental quality and climate change. A common policy to reduce this impact is payment for ecosystem services (PES) programs, where farmers receive payments if they implement particular conservation practices. Despite the importance of these programs, existing evaluations of their additionality (i.e., whether treated farmers would have adopted the conservation practice without the incentive payments) are surprisingly inadequate, as they rely on an assumption of selection on observables (i.e., unconfoundedness). Since farmers can only receive payments if they adopt a conservation practice, unconfoundedness is almost guaranteed not to hold. We develop a selection model to re-evaluate the additionality of PES programs and document large biases in previous estimates.

JEL codes: Q24, D04, C50; Keywords: Environmental policy, Payment for ecosystem services programs, Additionality, Selection on unobservables.

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1 Introduction

Modern agricultural production has significant and wide-ranging impacts on environmental quality. Land use change from extensive cultivation drives changes in rainfall and surface temperatures (Maeda et al., 2021). Intensive tillage, burning crop residues, and livestock production contribute to air pollution-related morbidity and mortality (Domingo et al., 2021). Overuse of chemical fertilizers has resulted in nitrogen emissions in excess of so-called "planetary boundaries," threatening terrestrial and aquatic ecosystems and human health (Schulte-Uebbing et al., 2022) and contributing significantly to global climate change (Lawrence et al., 2021).

Payment for ecosystem services (PES) programs are one widely-used policy tool for reducing the environmental impact of farming. These programs offer financial support in the form of direct payments to subsidize farmers' voluntary adoption of "conservation practices" that reduce deforestation, water and air pollution, and greenhouse gas emissions, among other goals. Receipt of PES is contingent on a farmer having committed to adopt a particular practice. PES account for billions of dollars in government spending each year worldwide (Le et al., 2024). A prominent example in the U.S. is the Environmental Quality Incentives Program (EQIP), which allocates $1.76 billion in payments to US farmers annually to subsidize conservation practice implementation on cultivated lands (Natural Resource Conservation Service, 2020).

The "additionality" of PES captures the effectiveness of these programs in increasing the adoption of conservation practices among farmers. Additionality is determined by the fraction of participating farmers who would have adopted the practice without receiving any payment. In traditional econometric terms, it is therefore an "average treatment effect on the treated." Measuring additionality is critical for efficient PES program design and evaluation (e.g., Aspelund and Russo, 2024; Canales, Bergtold, and Williams, 2024; Miao et al., 2023).

Despite the importance of PES programs and the central role that additionality plays in evaluating and designing these programs, the methods that have been used for estimating additionality are surprisingly inappropriate for the task. Existing estimates of the additionality of PES programs use treatment effects estimators that rely on "selection on observables", i.e., on an assumption of unconfoundedness (Velly and Dutilly, 2016), including matching estimators (Alix-Garcia, Shapiro, and Sims, 2012; Arriagada et al., 2012; Jones and Lewis, 2015; Mezzatesta, Newburn, and Woodward, 2013; Sawadgo and Plastina, 2021; Claassen, Duquette, and Smith, 2018), inverse propensity score weighting (Woodward, Newburn, and Mezzatesta, 2016), and regression adjustment (Velly, Sauquet, and Cortina-Villar, 2017). These estimators rely on comparing farmers who receive incentive payments through a PES program with farmers who do not receive the payment but exhibit similar observed characteristics, attributing the difference in average adoption rates for the conservation practice between these farmers to the causal effect of the PES program. However, unconfoundedness is almost guaranteed not to hold given the contingent nature of PES program participation since any factor that determines the adoption of the conservation practice—whether observed or unobserved to the econometrician—will also determine participation. Previous work therefore does not properly identify the additionality of PES.[1]

We propose a new approach to identifying the additionality of PES that relies on a selection model (see, e.g., Heckman and Vytlacil (2007a), Heckman and Vytlacil (2007b), or Mogstad and Torgovitsky (2018) for reviews). We model farmers as adopting a conservation practice if net benefits are positive. PES programs increase net benefits by tying adoption to an incentive payment. Our approach first allows us to clearly outline the deficiencies of other approaches that rely on an assumption of selection on observables. Second, it allows us to provide more credible estimates of the additionality of PES programs. The core of our identification strategy is the empirical observation that a significant share of

[1]In addition to policy evaluation, our work has important implications for corporate carbon offsets, as many programs offer carbon credits based on the same additionality estimates that we argue to be inappropriate. One example is the Verified Carbon Standard, the most widely used greenhouse gas crediting program, which relies on matching to calculate the additionality of PES programs (Verra (2024)). A similar issue arises in the context of renewable electricity generation investments. There, Calel et al. (2021) have documented issues with existing estimates of additionality by leveraging the availability of observed measures of profitability. These measures are generally not available in the context of agricultural conservation practices, hence the need for the alternative approach proposed here.

farmers adopts the conservation practices under consideration without receiving an incentive payment. We model this finding as some farmers not knowing about the PES program or not being interested in participating (henceforth, "consideration") or not being eligible for the program ("eligibility").[2] We then impose an assumption of unconfoundedness on consideration/eligibility rather than on participation in the program itself. If consideration/eligibility status were observed, we could use it as an instrumental variable (IV) and we would be in a standard binary IV setting. Unfortunately, typical datasets, including ours, do not provide access to such information. Instead, we show that under an exclusion restriction — there is some observed covariate that correlates with adoption decisions but not with consideration/eligibility — we can identify our selection model and recover the same estimand, additionality, as if eligibility/consideration were observed.

Our approach provides a method for estimating additionality of PES programs that (i) explicitly accounts for the contingent nature of participation in PES programs and (ii) can be implemented on the typical datasets that are used for the evaluation of these programs. Applying our method to EQIP, we find that previousstudies severely overestimate the additionality of PES programs. This is intuitive since only controlling for observed covariates will not lead to comparable treatment and control groups when selection into treatment is determined by the outcome of interest itself. To our knowledge, the only other work that tackles this issue is Aspelund and Russo (2024), who use auction bid data to estimate the additionality of a different PES program, the Conservation Reserve Program. Our analysis complements that of Aspelund and Russo (2024). Both establish that current evaluation methods can be severely biased. While Aspelund and Russo (2024) have access to auction bid data, which naturally provides quasi-experimental variation by comparing farmers with winning bids with farmers who placed the next-best bid, the advantage of our analysis is that it can be applied in settings where policy makers or economists only have access to the kind of survey data that is typically used for evaluation and to evaluate PES

[2]If a farmer had already adopted the conservation practice under consideration and was eligible for and considered participating in the program, they would be foregoing a costless payment by not opting into EQIP.

programs that do not rely on auctions for allocation (such as, e.g., EQIP).[3]

2 EQIP, Conservation Practices, and the ARMS Dataset

The goal of EQIP is to reduce the environmental impact from agricultural production by reducing water and air pollution and soil erosion, promoting wildlife habitat and soil health, and increasing producers' resilience against climate change. EQIP accomplishes these goals by supporting farmers' adoption of conservation practices through free technical assistance and subsidies, referred to as "cost share" payments. Farmers interested in applying for EQIP funding must work with the NRCS to develop a conservation plan outlining resource concerns for their farm and proposing relevant conservation practices to address these concerns. Each state-level NRCS office ranks applications according to private criteria. Farmers selected for funding receive cost share payments contingent on successfully implementing their proposed conservation practices (US Department of Agriculture Natural Resources Conservation Service, 2024b). Cost share payments are practice-specific, vary from state to state, and cover 75% of the average cost of implementing each practice, as estimated at the state level by each state's NRCS office. Importantly, transactions costs of applying for cost shares can be nontrivial (McCann and Claassen, 2016), and estimated cost share rates do not account for these costs. Larger cost shares and advance payments are available for historically underserved producers, including beginning, socially disadvantaged, and veteran farmers. Application is open to landowners and renters of conventional and organic farmland producing either specialty or commodity crops, forest products, or livestock.

EQIP supports dozens of distinct conservation practices. We focus on two of the most common practices in the data we observe (described later): no-till (NT) and nutrient management (NM). As the name implies, NT involves foregoing tillage following harvest; crop residues are instead left on the field surface. NT reduces soil erosion and eliminates the need to make several tillage passes with heavy cultivating equipment, reducing farmers'

[3]Beyond estimating additionality, Aspelund and Russo (2024) also discuss market design in the context of the Conservation Reserve Program, which is not addressed at all in this paper.

input and labor costs—particularly fuel (Claassen et al., 2018). Adopting NT may reduce subsequent crop yields, although evidence for this is mixed (Chen, Gramig, and Yun, 2021). NM involves developing a nutrient management plan to more optimally manage fertilizer rates and application timing. NM is meant to reduce nutrient runoff to waterways as well as farm-level nutrient use. Private costs of NM to adopting farmers include soil testing costs and reduced crop yields (Marshall et al., 2018).

We collect farm-level data on conservation practice adoption from the USDA's annual Agricultural Resource Management Survey (ARMS). The survey contains data from a nationally-representative sample of US farmers. Data collection occurs over three "phases." The first phase, conducted in early summer each year, screens farmers for eligibility. ARMS targets farms growing specific commodities each year, and hence phase 1 mainly ensures respondents are qualified as farmers raising the targeted commodities. In phase II, conducted each fall, respondents answer questions related to production on one of their farm fields,[4] including questions about conservation practice adoption and funding, nutrient application, and field features. Phase III, in late winter, collects farm-level data on commodity marketing and income, operating and capital expenditures, farm assets and debts, and farmer characteristics. Due to its exhaustive nature and national scope, prior work has used ARMS data to benchmark the additionality of federal conservation programs in the US (Claassen, Duquette, and Smith, 2018; Claassen and Duquette, 2014).

We use data from three years: 2016, 2017, and 2018. Surveys these years targeted producers growing corn, wheat, and soybeans, respectively. These crops represent 53% of total crop acreage in the US and are therefore the targets of the majority of conservation programs (US Department of Agriculture National Agricultural Statistics Service, 2017). From the phase II field-level survey, we collect information on conservation practice adoption, particularly whether the farmer has adopted NT or NM, whether those practices receive EQIP funding, and if adoption of the practice is a part of compliance requirements

[4]Large farms in the US commonly comprise multiple distinct fields, which may grow different crops under different prodution practices. ARMS surveyors randomly choose one of a respondent farmer's fields and ask questions about practices only on that field.

to receive other forms of federal aid.[5] We also use data on whether the field is classified as highly erodible and whether the farmer owns the field or not. Land ownership is an important consideration for conservation practice adoption as landowners can internalize the long-term benefits from resulting improvements in soil health and productivity, whereas renters may not (Prokopy et al., 2008; Knowler and Bradshaw, 2007). From the phase III farm-level survey, we obtain data on total acres in operation, farmers' demographics, including age and whether farming is the main source of income for the respondent's household. We merge this farm-level data from ARMS with external data, including a county-level productivity index for corn, soybeans, and small grains from the Gridded Soil Survey Geographic database (US Department of Agriculture Natural Resources Conservation Service, 2024a), state-level EQIP cost-share rates and practice cost estimates (US Department of Agriculture Natural Resources Conservation Service, 2024c), and state-level data on diesel fuel and natural gas prices from the US Energy Information Administration. Diesel fuel and natural gas prices may be important components of the private benefits of NT and NM to farmers.[6] Conversely, productivity index may be an important driver of the private costs of adopting NT or NM if these conservation practices decrease yields and farmers with more productive soils stand more to lose from adopting the practice. ARMS includes probability weights calculated to ensure representativeness of the final sample. Tables 3 and 4 in the Appendix show the weighted means of each variable used in our analysis.

We emphasize two salient features of our data and PES programs more generally. The first is the contingent nature of the cost share payments: farmers are free to adopt a conservation practice in the absence of payment, but *must* adopt conditional on receiving a cost share. Hence, unconfoundedness (conditional independence of adoption decisions and participation in EQIP) cannot hold here and treatment effects estimates from approaches that impose this assumption—including matching, inverse probability weighting, and re-

[5] Access to federal assistance such as subsidized crop insurance can be contingent on the adoption of conservation practices when farming highly erodible soil or other sensitive lands. These contingencies are distinct from the EQIP program and therefore our analysis will "control" for these external requirements to adopt conservation practices.

[6] Nutrient management will allow farmers to use less fertilizer, and natural gas price is a key determinant of fertilizer price because natural gas is a key input to nitrogen fertilizer production (Ibendahl, 2020).

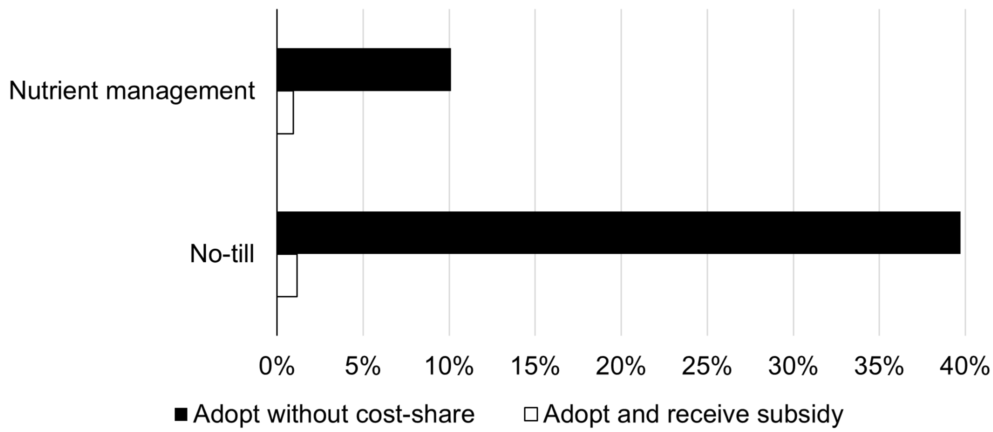

Figure 1: Adoption and EQIP participation among ARMS sample farmers by practice

gression adjustment—will yield biased estimates of additionality. (Although this assertion is intuitive, we demonstrate it rigorously below and show that previous estimates are likely to overstate additionality.) Second, a nontrivial proportion of farmers adopt NT or NM without receiving a cost share (Figure 1). We interpret this as heterogeneity in farmers' consideration of participating in EQIP (e.g., due to differences in transactions costs, awareness, or farmer perception of the practices), or eligibility for the program.[7] In the next section, we show that this variation in consideration/eligibility can be used as a source of exogenous variation in program participation. We show that this occurs even though consideration/eligibility is not directly observed by the researcher, being instead only inferred for farmers who participate in the program (so that they considered and were eligible for EQIP) and for farmers who did not participate but adopted the practice (so that they did not consider EQIP or were ineligible).

[7]EQIP has very few eligibility requirements, and hence we expect this variation to mostly originate from consideration of EQIP. To participate in EQIP, producers must must be "(1) A person, legal entity, Indian Tribe, Alaska Native corporation, or joint operation with signature authority or (2) engaged in agricultural production or forestry management or have an interest in the agricultural or forestry operation associated with the land offered for enrollment... and be within applicable EQIP payment limitations" (US Department of Agriculture Natural Resources Conservation Service, 2023). What we dub eligibility could also capture farmers unsuccessfully applying for the EQIP program, so that they were *ex post* ineligible for it.

3 An Alternative Identification Strategy: Exogenous Latent Variation in Participation

We start from a simple model for whether a farmer i adopts a conservation practice in the absence of a cost share. Let $D_i = 1$ if the farmer receives the cost share payment and zero otherwise. Let $Y_i(d)$ denote the farmer's decision to adopt the practice given $D_i = d$, where $Y_i(\cdot) = 1$ if the farmer adopts and zero otherwise. Then

$$Y_i(0) = 1[b_i - c_i \geq 0],$$

where b_i and c_i denote the benefit and cost of the practice, respectively, so that a farmer adopts the practice if it yields positive net benefits. Given a cost share π_i, the farmer would adopt the conservation practice and accept the cost share payment if the resulting net benefits are positive:

$$Y_i(1) = 1[b_i - c_i + \gamma_0\pi_i \geq 0],$$

where $\gamma_0 \geq 0$ is the marginal utility of money.[8]

If there were no frictions or restrictions on farmers' participation into EQIP, we would only observe two profiles of adoption Y_i and participation D_i: (i) adopt and participate, $(Y_i, D_i) = (1, 1)$, for farmers for whom $b_i - c_i + \gamma_0\pi_i \geq 0$, and (ii) neither adopt nor participate, $(Y_i, D_i) = (0, 0)$, for farmers for whom $b_i - c_i + \gamma_0\pi_i < 0$.

Recall, however, that we observe a significant share of farmers adopting the conservation practice without receiving EQIP payments. We model this variation by introducing a latent variable that governs a farmer's consideration of and eligibility for EQIP, $E_i^\star$. A farmer i will only consider the program and be eligible if $E_i^\star = 1$. Identification will then rely on (i) an unconfoundedness assumption on this latent variable $(Y_i(0), Y_i(1) \perp E_i^\star | X_i$, where X_i collects observed covariates) rather than unconfoundedness of participation in the

[8]Our assumption on the sign of γ_0 is logical both conceptually (the marginal utility of money should be positive) and empirically (no farmer would be observed participating in the EQIP program if this condition were violated).

program (D_i), which was the assumption imposed in previous evaluations of PES program additionality, and (ii) the availability of at least one covariate x_i that is related to net benefits $b_i - c_i$ without driving variation in eligibility $E_i^\star$.

For expositional simplicity, we will articulate the issues that arise with existing methods and our proposed identification strategy in a simplified setting where a single covariate x_i drives variation in net benefits and there is no variation in incentive payment amounts ($\pi_i = \pi$).[9] Our simplified model takes the form

$$b_i - c_i = \alpha_0 + \beta_0 x_i - \epsilon_i, \qquad E_i^\star = 1[\nu_i \leq 0], \tag{1}$$

where ϵ_i and ν_i denote idiosyncratic shocks to the private net benefits of adoption and to eligibility/consideration, respectively. We further assume

$$\epsilon_i | x_i \sim N(0,1),\ \nu_i \perp \{x_i, \epsilon_i\}. \tag{2}$$

The second assumption in (2) captures our assumption of unconfoundedness on eligibility since it implies that $(Y_i(1), Y_i(0)) \perp E_i^\star | x_i$. We use the normality assumption in (2) here and in our empirical implementation below, but the online appendix provides conditions under which our model of selection is identified without parametric restrictions on the distributions of the shocks ϵ_i or ν_i. Our exclusion restriction is complete by further requiring $\beta_0 \neq 0$, so that the covariate x_i does have a non-zero relationship with the net benefits of adoption.

[9] In the next section, we will explicitly account for variation across farmers in payment rates π_i and additional covariates in both the adoption model and consideration model. This additional variation will help with establishing identification since (i) variation in payment rates provides additional identifying variation, as discussed in the online appendix, and (ii) the availability of control covariates allows for our assumption of unconfoundedness on eligibility/consideration to be more plausible. For the discussion of identification in the simplified setting used in this section, one can think of the model being already conditional on payment rates and additional covariates so that we only exploit the variation in one excluded covariate x_i for identification.

We then obtain a model for the observed outcomes, (Y_i, D_i):

$$(Y_i, D_i) = \begin{cases} (1,1) & \text{if } \alpha_0 + \beta_0 x_i + \gamma_0 \pi \geq \epsilon_i,\ \nu_i \leq 0, \\ (1,0) & \text{if } \alpha_0 + \beta_0 x_i \geq \epsilon_i,\ \nu_i > 0, \\ (0,0) & \text{otherwise.} \end{cases} \tag{3}$$

In this simplified setting, we will show that additionality is identified as long as the covariate x_i has at least three points of support, which, without loss of generality, we label as $\{0, 1, 2\}$. First, we establish formally that existing methods that are predicated upon an assumption of unconfoundedness on program participation D_i itself will overstate the level of additionality of contingent participation programs such as EQIP.

3.1 Failure of unconfoundedness

While we impose an assumption of unconfoundedness on the latent variable $E_i^\star$, which indexes a farmer's consideration of EQIP program, participation in EQIP itself (D_i) is not conditionally independent of adoption decisions Y_i:

$$\begin{aligned} E(Y_i(0)|D_i = 1, x_i) &= \frac{\Phi(\alpha_0 + \beta_0 x_i)}{\Phi(\alpha_0 + \beta_0 x_i + \gamma_0 \pi)}, \\ &> E(Y_i(0)|D_i = 0, x_i) = \frac{\Phi(\alpha_0 + \beta_0 x_i)(1 - F_\nu(0))}{1 - \Phi(\alpha_0 + \beta_0 x_i + \gamma_0 \pi) F_\nu(0)}, \end{aligned}$$

where $F_{\nu_i}(.)$ denotes the cumulative distribution of ν_i.

This establishes the inadequacy of the assumption of unconfoundedness for participation in EQIP and corresponding evaluation methods and shows that these methods will exhibit positive biases. Intuitively, this is because "treated" farmers (with $D_i = 1$) and "untreated" farmers (with $D_i = 0$) exhibit differences not only in terms of the observed covariates that drive net benefits of adoption (x_i) but also in terms of the unobserved factors that drive adoption. Specifically, treated farmers satisfy the condition $\epsilon_i \leq \alpha_0 + \beta_0 x_i + \gamma_0 \pi$, whereas among untreated farmers we will have a mixture between $\epsilon_i > \alpha_0 + \beta_0 x_i + \gamma_0 \pi$ (for farmers who considered participation in the program but opted not to participate) and ϵ_i being drawn from its unconditional distribution (for farmers who didn't consider participation in the program).

3.2 Identification in the simplified setting

We now discuss identification of our approach in the simplified setting constructed above. First note that, if there was no variation in consideration, the effect of the incentive payments would not be identified. If every farmer were eligible and considered EQIP ($E_i^\star = 1 \; \forall \, i$), we would only observe the probability of jointly adopting the conservation practice and participating, $\Phi(\alpha_0 + \beta_0 x_i + \gamma_0 \pi)$. With a single value of payment rates, π, it would be impossible to separate the effect of the treatment on adoption, $\gamma_0 \pi$, from the intercept, α_0. Here, we show that variation in consideration or eligibility across farmers, together with our assumption of conditional independence and the exclusion restriction on x_i, yield identification of the additionality of EQIP cost shares when using the correct contrasts in the probability of adopting the conservation practice with and without cost shares.

To shorten notation, we write $P((j,j^{'})|x)$ to denote $P((Y,D) = (j,j^{'})|x_i = x)$, for $j, j^{'} \in \{0,1\}$. Our model then implies the following mapping for these conditional probabilities:

$$P((1,1)|x) = \Phi(\alpha_0 + \beta_0 x + \gamma_0 \pi) F_\nu(0),$$
$$P((1,0)|x) = \Phi(\alpha_0 + \beta_0 x)(1 - F_\nu(0)).$$

Ratios in the conditional probabilities $P((1,0)|x)$ at various values of $x \in \{0,1,2\}$ identify the intercept α_0 and the slope coefficient β_0 because the equations

$$\frac{P((1,0)|0)}{P((1,0)|2)} = \frac{\Phi(\alpha_0)}{\Phi(\alpha_0 + 2 \cdot \beta_0)}, \qquad \frac{P((1,0)|1)}{P((1,0)|2)} = \frac{\Phi(\alpha_0 + \beta_0)}{\Phi(\alpha_0 + 2 \cdot \beta_0)}, \tag{4}$$

uniquely identify β_0 and α_0.[10] This implies that the probability of adopting without incentive payments, $P(Y(0) = 1|x) = \Phi(\alpha_0 + \beta_0 x)$, is identified, and thus so is the probability of

[10]We provide the steps for this result in the online appendix.

considering the program, $F_\nu(0) = 1 - \frac{P((1,0)|x)}{\Phi(\alpha_0+\beta_0 x)}$. Given identification of $F_\nu(0)$, we can then identify $P(Y(1)=1|x) = \frac{P((1,1)|x)}{F_\nu(0)} = \Phi(\alpha_0+\beta_0 x+\gamma_0\pi)$ for all values of x. We can therefore identify the additionality of EQIP, i.e., its effect on treated farmers' adoption decisions, by comparing rescaled probabilities of adoption with and without incentive payments:

$$\begin{aligned} ATT(x_i) &= E\left(Y_i(1) - Y_i(0)|D_i = 1, x_i\right) \\ &= 1 - \frac{\Phi(\alpha_0+\beta_0 x)}{\Phi(\alpha_0+\beta_0 x+\gamma_0\pi)} \\ &= 1 - \frac{P(1,0|x)/P(E^\star=0)}{P(1,1|x)/P(E^\star=1)}. \end{aligned} \tag{5}$$

3.3 Interpretation of the estimand

We can compare the estimand in (5) with the LATE estimand of Imbens and Angrist (1994) that would be obtained if the researcher actually observed the latent variable $E_i^\star$ that determines consideration of or eligibility for EQIP. Under the assumption of conditional independence ($E_i^\star \perp Y_i(0)|x_i$), a natural approach to estimation would be to use an instrumental variable approach, relying on the exogenous variation in consideration/eligibility to identify the effect of EQIP on adoption,

$$\Delta_{\text{Wald}} = \frac{E(Y|E^\star=1,x) - E(Y|E^\star=0,x)}{E(D|E^\star=1,x) - E(D|E^\star=0,x)}.$$

This expression identifies a particular local average treatment effect: the average effect of the conservation program on "compliers." In our setting, compliers are simply all farmers who participate in the program. This is because compliers are farmers who would not have participated in the program if not eligible or not considering the program (all farmers), and who would participate in the program if eligible or considering the program (i.e., farmers observed participating in the program since participation is not possible without being eligible). Therefore, in our setting, Δ_{Wald} identifies the average treatment effect of the conservation program on the treated, i.e., its additionality:

$$\begin{aligned}\Delta_{\text{Wald}} &= \frac{P(Y=1|E^\star=1,x) - P(Y=1|E^\star=0,x)}{P(Y=1|E^\star=1,x)} \\ &= 1 - \frac{P(Y=1|E^\star=0,x)}{P(Y=1|E^\star=1,x)}.\end{aligned}$$

Under the assumptions of our selection model above, this expression is identical to (5).

Intuitively, we can think of the selection model outlined above as imposing enough structure that one can identify the same estimand as with an (infeasible) instrumental variable regression of adoption on program participation that would use (actually unobserved) program eligibility / consideration as an instrumental variable.

4 Re-Estimating the Additionality of EQIP

We now outline the empirical implementation of the identification strategy described in the previous section. Let $X_{y,i} = \left[x^1_{y,i} \cdots x^K_{y,i}\right]$ and $X_{d,i} = \left[x^1_{d,i} \cdots x^M_{d,i}\right]$ collect covariates explaining adoption and consideration/eligibility, respectively. Then our model of selection for farmer i in state s becomes

$$(Y_i, D_i) = \begin{cases} (1,1) & \text{if } X_{y,i}\beta_0 + \gamma_0(\pi_s - C_s) \geq \epsilon_i,\ X_{d,i}\theta_0 \geq \nu_i, \\ (1,0) & \text{if } X_{y,i}\beta_0 - \gamma_0 C_s \geq \epsilon_i,\ X_{d,i}\theta_0 < \nu_i, \\ (0,0) & \text{otherwise,} \end{cases} \qquad (\nu_i, \epsilon_i)|X_{y,i}, X_{d,i}, \pi_s, C_s \sim N(0, I_2). \tag{6}$$

We explicitly account for a farmer's state, s, because the variation in incentive payments by EQIP, π_s, occurs at the state-level. Our model also includes state-level estimates of practice costs, C_s, as a driver of adoption. These estimates are provided by the U.S. Department of Agriculture ((US Department of Agriculture Natural Resources Conservation Service, 2024c)) and determine payment rates with a simple cost-share rule of 75%: $\pi_s = 0.75 \times C_s$.

Including these cost estimates in our model allows us to account for state-level unobserved variation in the cost of each conservation practice. To see this, assume each farmer's cost of adopting a given practice is

$$c_i = f_s + X_{y,i}\delta_0 + u_i, \qquad\qquad E(u_i|X_{y,i}) = 0,$$

where f_s captures state-level variation in costs, δ_0 captures the effect of the covariates in $X_{y,i}$ on cost, and u_i captures idiosyncratic unobserved variation. We then take into account that EQIP payment rates are based on state-level estimates of average cost:

$$\begin{aligned} C_s &= E\left(c_i|s_i = s\right), \\ &= f_s + E(X_{y,i}|s_i = s)\delta_0, \end{aligned} \tag{7}$$

where s_i is farmer i's state.

We can then obtain:

$$c_i = C_s + (X_{y,i} - E(X_{y,i}|s_i = s))\delta_0 + u_i,$$

and we therefore account for unobserved state-level variation in cost (f_s) by simply including the EQIP cost estimates in our list of covariates, together with the state-level averages of each of our farmer-specific covariates.[11] For notational simplicity, we define the list of covariates $X_{y,i}$ in (6) to include these state-level averages.

The covariates included in $X_{y,i}$ are (in addition to a constant and, where applicable, state-level averages): diesel price (for NT) or natural gas price (for NM), whether the farmed soil is classified as highly erodible, operation size (in acres), whether the field is owned by the farmer, the state-level productivity index for the field's crop selection, the farmer's age, an indicator for whether the conservation practice under consideration is necessary for

[11] Note that these state-level averages should be included as separate covariates rather than including farmer-level covariates deviated from their state-level averages since the same covariates $X_{y,i}$ may also have a predictive effect on benefits $b_{s,i}$ in addition to being predictive of cost c_i.

the farmer to comply with a requirement for some other source of federal aid than EQIP (e.g., subsidized crop insurance), and an indicator variable for crop type (corn, soy, or wheat). The covariates included in $X_{d,i}$ are (in addition to a constant): EQIP payment rates, π_s, operation size, whether the respondent's occupation is mainly farming, and the highly erodible classification of the soil.

Our main exclusion restrictions, which, as discussed above, are central to our ability to identify the additionality of EQIP, are (i) diesel price for NT and natural gas price for NM, and (ii) soil productivity index. As discussed above, diesel price for NT and natural gas price for NM are potentially important drivers of the farmers' private benefits from adopting these practices. When adopting NT, farmers will avoid the need for multiple tilling passes and save the corresponding fuel costs. When adopting NM, farmers will potentially be able to reduce the amount of fertilizer they use, and natural gas prices are an important driver of fertilizer price as natural gas is one of the main inputs for the production of nitrogen fertilizer. Soil productivity can also be a determinant for the private net benefits of adoption. For instance, if either conservation practice leads to larger losses in yields on more productive soils, a farmer's private cost to adoption of the practice would be greater with more productive soil.

Our identifying exclusion restriction is that these variables affects farmers' adoption decisions but do not affect a farmer's eligibility for EQIP or a farmer's consideration of the program. Note that we include EQIP payment rates, π_s, in the consideration/eligibility equation, so that we allow for possible "saliency" effects, whereby a farmer is more likely to know about the program or consider applying for it if payment rates are high.

We can then estimate our model by maximum likelihood. Table 1 reports the maximum likelihood estimates of the parameters of this model for the no-till and nutrient management practices. We see that most variables have expected signs. In particular, diesel prices is estimated to be a strong driver for adoption decisions of NT, with higher diesel prices leading to more likely adoption of NT, which, as discussed above, is the expected direction of the effect. Interestingly, natural gas price is not estimated to have a statistically significant effect on adoption decisions of NM. This could be because NM does not lead to large enough decreases in the volume of fertilizer used (instead, affecting other variables like the timing or mode of application). However, productivity index is estimated to have a statistically significant effect on NM adoption, with farmers farming more productive soil being less likely to adopt NM than farmers farming less productive soil. This would indicate that farmers with more productive soil face greater losses in productivity (i.e., large private costs of adoption) when adopting NM. For NT, soil productivity has the opposite sign but is not estimated to be statistically significant. This could correspond to the ambiguous sign of the effect of NT on yields discussed above.

We can then proceed to estimating the additionality of EQIP on the adoption of the conservation practices NT and NM. Before reporting the results using our proposed method, we discuss results using the status-quo methods that have been used for the evaluation of PES programs. First, Table 2 reports a simple difference in means. We see that, since every "treated" farmer (i.e., every farmer who receives EQIP payments) is required to adopt the corresponding conservation practice (for an adoption rate of 100% among the treated), and since these conservation practices are relatively infrequent in the general population (approximately 40% for NT, and 10% for NM), a simple difference-in-means yields extremely large estimates of additionality for EQIP (60% for NT, 90% for NM). Second, Table 2 reports results on additionality using methods predicated upon an assumption of selection on observables, namely, using regression adjustment (RA) and inverse propensity score weighting (IPW). This adjustment for differences in the observed covariates between farmers who participate or do not participate in EQIP leads to significant differences in estimated additionality. EQIP is now estimated to have additionality of 40%-50% (depending of which method is used) for NT, and around 60% for NM.

As discussed above, these results are likely to overstate the additionality of EQIP for these conservation practices since farmers's decisions to participate in EQIP will not only be affected by the same observed covariates that affect their adoption of conservation practices, but also by the factors unobserved to the researcher that enter their adoption decisions.

The strength of our proposed method to identifying the additionality of EQIP or similar PES programs is to account for this selection on unobservables. In Table 2, we report the additionality of EQIP estimated using our method. Our estimates of additionality are significantly smaller than with RA or IPW, indicating that selection on unobservables does seem to be at play in these results. We estimate EQIP to have approximately 30% additionality for NT, but no significant additionality (7%) for NM. In Section C, we show that this finding of no additionality for NM is robust by discussing testable implications of our model jointly with the null hypothesis of no additionality of EQIP. We consistently fail to reject these implications for NM but not for NT.

5 Conclusion

Standard treatments of methods for program evaluation (e.g., Imbens and Rubin (2015) or Abadie and Cattaneo (2018)) often assist practitioners to find the correct framework by dividing methods into a menu of well-established categories that depend on features of the data/setting under consideration and beliefs of the researcher about their setting: (i) Randomized assignment, (ii) Selection on observables (unconfoundedness), (iii) Difference-in-differences, (iv) Instrumental variables, (v) Regression discontinuity design. Overall, this provides enormous value to our ability to evaluate programs in a interpretable and replicable way that mitigates the impact of personal priors or biases on final results. However, in some cases, standard methods may clearly not be suitable for impact evaluation.

A solution to this issue can be to obtain more data than currently available, which is done in Aspelund and Russo (2024) by obtaining auction data. Alternatively, researchers can rely on improved models for policy evaluation based on existing datasets. Here we show that a specific model of joint selection and adoption can yield convincing new results on the additionality of EQIP with the widely used ARMS dataset. Our method can directly be used to evaluate other payment for ecosystem services programs. Given the importance of these programs globally, both in terms of potential environmental impact and cost, we hope that the approach and evidence presented here guides future steps in the evaluation and design of these policies.

Table 1: Maximum likelihood estimates of the adoption and selection model.

	No-till		Nutrient management	
	Estimate	SE	Estimate	SE
Adoption equation				
Payment rates ($/ac), γ_0				
Diesel price ($/gal)			-	-
Natural gas price ($/000 ft3)	-	-		
Farmer age (yrs)				
Highly erodible				
ln(operation acres)				
Owned field				
Compliance				
Productivity index				
(Constant and state averages included but not reported for concision)				
Consideration equation				
Payment rate ($/ac)				
ln(operation acres)				
Mostly farmer = 1				
Highly erodible				
(Constant included but not reported for concision)				
Observations				
Log-likelihood				

Results currently being transferred from USDA's computing server.

Table 2: Estimates of additionality.

	No-till		Nutrient management	
	Additionality	SE	Additionality	SE
Selection model				
Difference-in-means				
RA				
IPW				

Results currently being transferred from USDA's computing server.

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APPENDIX

(FOR ONLINE PUBLICATION)

A Parametric Identification

In this section, we show that the equations in (4) uniquely identify the parameters α_0 and β_0. First, note that the sign of β_0 is identified from the comparison between $\frac{\Phi(\alpha_0)}{\Phi(\alpha_0+2\cdot\beta_0)} = \frac{P((1,0)|0)}{P((1,0)|2)}$ and 1, so that without loss of generality we can take $\beta_0 > 0$ to be known ($\beta_0 = 0$ is ruled out by our exclusion restriction, and if $\beta_0 < 0$ we could use the same steps as below to identify $\alpha_0^{'} = \alpha_0 + 2 \cdot \beta_0$ and $\beta_0^{'} = -\beta_0$).

It will be notationally convenient to define $\delta_1 = \frac{P((1,0)|0)}{P((1,0)|2)}$, $\delta_2 = \frac{P((1,0)|1)}{P((1,0)|2)}$, so that $0 < \delta_1 < \delta_2 < 1$ under $\beta_0 > 0$, and to show identification of α_0 and $\tau_0 = \alpha_0 + 2 \cdot \beta_0$.

With this notation, the first equation in (4) is rewritten as

$$\frac{\Phi(\alpha_0)}{\Phi(\tau_0)} = \delta_1,$$

and we have

$$\alpha_0 = \Phi^{-1}(\delta_1 \Phi(\tau_0)). \tag{A.1}$$

Substituting this identity into the second equation in (4), we have

$$\frac{\Phi(\frac{\tau_0+\Phi^{-1}(\delta_1\Phi(\tau_0))}{2})}{\Phi(\tau_0)} = \delta_2. \tag{A.2}$$

However, the function $f : y \to \frac{\Phi(\frac{y+\Phi^{-1}(\delta_1\Phi(y))}{2})}{\Phi(y)}$ is strictly increasing in y for any value $\delta_1 \in (0, 1)$, so that (A.2) uniquely identifies τ_0, so that (A.1) identifies α_0, which establishes the desired result.

B Non-Parametric Identification

In this section we discuss the identification of our model of selection without parametric restrictions on the distribution of the unobserved shocks to adoption and eligibility/consideration (ϵ and ν). For simplicity we will consider the special case where X is a scalar covariate as all results extend to the multivariate case in a straightforward way (e.g., by reproducing the argument below while explicitly conditioning on the rest of the covariates). In addition, we will be leveraging variation in the payment rates Π to obtain identification in this setting, while allowing for these payment rates to affect both adoption decisions when participating in the incentive payment program and eligibility/consideration. In this setting, our model of adoption and selection is therefore given by:

$$(Y,D)=\begin{cases}(1,1) & \text{if } \beta_0 X+\gamma_0\Pi-\epsilon\geq 0 \text{ and } \zeta_0\Pi-\nu\geq 0,\\ (1,0) & \text{if } \beta_0 X-\epsilon\geq 0 \text{ and } \zeta_0\Pi-\nu<0,\\ (0,0) & \text{otherwise.}\end{cases}$$

As in the main text, we maintain the assumptions of independence:

$$\epsilon,\nu\perp X,\Pi \text{ and } \epsilon\perp\nu$$

and we let F_ϵ and F_ν denote the cumulative distribution functions of ϵ and ν.

Note that our exclusion restriction also implies $\beta_0\neq 0$. Without loss of generality, we will take $\beta_0>0$, since if $\beta_0<0$ we could redefine the covariate $X=-X$ to obtain $\beta_0>0$.[1] In this section we will also assume that:

1. The distribution functions of ϵ and ν have well-defined and strictly positive probability density functions, f_ϵ and f_ν, with respect to the Lebesgue measure.

2. (X,Π) are continuously distributed random variables with support given by $[x_{\min},x_{\max}]\times[\pi_{\min},\pi_{\max}]$ and strictly positive probability density function. The conditional variances $\mathrm{Var}(X|\Pi)$, $\mathrm{Var}(\Pi|X)$ are both strictly positive over the entire support of Π and X (i.e., these two covariates are not collinear). In addition, the support of (X,Π) includes two points (x,π) and $(x+\frac{\gamma_0}{\beta_0}\pi,\pi)$ such that $F_\epsilon(\beta_0 x+\gamma_0\pi)>0$, $F_\nu(\zeta_0\pi)\in(0,1)$.

3. The data observed by the researcher is obtained by random sampling.

4. There are two points on the support of (X,Π), (x',π) and (x,π), such that $\frac{f_\epsilon(\beta_0 x+\gamma_0\pi)}{F_\epsilon(\beta_0 x+\gamma_0\pi)}\neq\frac{f_\epsilon(\beta_0 x'+\gamma_0\pi)}{F_\epsilon(\beta_0 x'+\gamma_0\pi)}$ (and both ratios are well-defined, i.e., $F_\epsilon(\beta_0 x+\gamma_0\pi), F_\epsilon(\beta_0 x'+\gamma_0\pi)>0$).

Conditions 1-3 are standard and impose regularity conditions on the identification problem studied in this section. Condition 4 is not a necessary condition but it provides a simple condition to guarantee that identification of the (normalized) marginal utility parameter

[1] As in Section A, the sign of β_0 is identified from $P((Y,D)=(1,0)|X=x,\Pi=\pi)$ for two different values of x, holding π constant.

$\frac{\gamma_0}{\beta_0}$ by ruling out scenarios where the cumulative distribution of ϵ, F_ϵ, and its derivative, f_ϵ, have a linear relationship across the entire support of $\beta_0 X + \gamma_0 \Pi$. One could stipulate conditions other than Condition 4 above to guarantee that $\frac{\gamma_0}{\beta_0}$ is identified, with the steps below following identification of $\frac{\gamma_0}{\beta_0}$ remaining unchanged.[2]

To shorten notation, define $P((j,j^{'})|x,\pi) = P((Y,D) = (j,j^{'})|X = x, \Pi = \pi)$. As discussed above, we can take $\beta_0 > 0$. We can therefore normalize β_0 to $\beta_0 = 1$ (by redefining $\gamma_0 = \frac{\gamma_0}{\beta_0}$ and $\epsilon = \frac{\epsilon}{\beta_0}$).

With this normalization, our model implies:

$$P(1,1|x,\pi) = F_\epsilon(x + \gamma_0\pi)F_\nu(\zeta_0\pi),$$

$$P(1,0|x,\pi) = F_\epsilon(x)(1 - F_\nu(\zeta_0\pi)),$$

and

$$\log(P(1,1|x,\pi)) = \log(F_\epsilon(x + \gamma_0\pi)) + \log(F_\nu(\zeta_0\pi)).$$

Under the assumptions above, these log-conditional probabilities are identified and so are their derivatives

$$\delta_1(x,\pi) := \frac{\partial}{\partial x}\log(P(1,1|x,\pi)) = \frac{f_\epsilon(x+\gamma_0\pi)}{F_\epsilon(x+\gamma_0\pi)},$$
$$\delta_2(x,\pi) := \frac{\partial}{\partial \pi}\log(P(1,1|x,\pi)) = \gamma_0\frac{f_\epsilon(x+\gamma_0\pi)}{F_\epsilon(x+\gamma_0\pi)} + \zeta_0\frac{f_\nu(\zeta_0\pi)}{F_\nu(\zeta_0\pi)}.$$

For two points (x,π) and $(x^{'},\pi)$ on the support of (X,Π), we then have:

$$\gamma_0 = \frac{\delta_2(x^{'},\pi) - \delta_2(x,\pi)}{\delta_1(x^{'},\pi) - \delta_1(x,\pi)},$$

where $\delta_1(x^{'},\pi) - \delta_1(x,\pi) \neq 0$ is guaranteed by Condition 4 above, which identifies γ_0.

Given identification of γ_0, for a value of π (guaranteed to exist by Condition 3) such that (i) $F_\nu(\zeta_0\pi) \in (0,1)$ and (ii) there is a value x with (x,π) and $(x+\gamma_0\pi,\pi)$ both belonging to the support of (X,Π), we have:

$$\frac{F_\nu(\zeta_0\pi)}{1 - F_\nu(\zeta_0\pi)} = \frac{P((1,1)|x,\pi)}{P((1,0)|x+\gamma_0\pi,\pi)},$$

and $F_\nu(\zeta_0\pi)$ is uniquely identified by $\frac{F_\nu(\zeta_0\pi)}{1-F_\nu(\zeta_0\pi)}$. Given identification of $F_\nu(\zeta_0\pi)$ for one value

[2] For instance, $\zeta_0 \geq 0$ could replace Condition 4 as a sufficient condition for identification if payment rates are also positive, $\pi \geq 0$ (which is the case in our application).

π, we then identify $F_\epsilon(x)$ for all values x on the support of X since

$$F_\epsilon(x) = \frac{P((1,0)|x,\pi)}{1 - F_\nu(\zeta_0\pi)}.$$

Given identification of $F_\epsilon(x)$ for all values x on the support of X, we can identify

$$F_\nu(\zeta_0\pi) = 1 - \frac{P((1,0)|x,\pi)}{F_\epsilon(x)}, \qquad F_\epsilon(x+\gamma_0\pi) = \frac{P((1,1)|x,\pi)}{F_\nu(\zeta_0\pi)},$$

for all values (x,π) on the support of (X,Π). Therefore, conditional average treatment effects on the treated (i.e., additionality) are identified without parametric restrictions on the distribution functions of ϵ and ν:[3]

$$CATT(x,\pi) = 1 - P(\epsilon \le x \,|\, \epsilon \le x + \gamma_0\pi) = 1 - \frac{F_\epsilon(x)}{F_\epsilon(x+\gamma_0\pi)}.$$

C Testable Implications of our Model in the Absence of Treatment Effects

In this section, we discuss testable implications of our model in the case where there are no treatment effects from the conservation incentive program.

Recall our model above, but without treatment effects, so that adoption (Y) and selection into the incentive program (D) are determined by:

$$(Y,D) = \begin{cases} (1,1) & \text{if } X\beta_0 \ge \epsilon, X_1\eta_0 \ge \nu, \\ (1,0) & \text{if } X\beta_0 \ge \epsilon, X_1\eta_0 < \nu, \\ (0,0) & \text{otherwise,} \end{cases}$$

where, as before, $\{\epsilon,\nu\} \perp X$ and $\epsilon \perp \nu$.

Let $F_\epsilon(.)$ and $F_\nu(.)$ denote the cumulative distribution functions of ϵ and ν. For all values of x, we obtain:

$$P(1,1|x) = F_\epsilon(x\beta_0)F_\nu(x_1\eta_0)$$
$$P(1,0|x) = F_\epsilon(x\beta_0)(1 - F_\nu(x_1\eta_0)),$$

where, as before, $P(j,j'|x)$ denotes $P((Y,D) = (j,j')|X = x)$, and $x = (x_1, x_2)$, where x_1 denotes the covariates that enter the eligibility/consideration equation, while x_2 are the

[3] Note that, as in the main text, we take $\gamma_0 \ge 0$ here, since having a positive marginal utility of money is a natural restriction in our selection model.

excluded covariates that only enter the adoption equation.

Under the null hypothesis of no treatment effects, we can obtain a simple non-parametric estimator of the conditional probability of being eligible for the conservation incentive program:

$$P(D=1|Y=1,X=(x_1,x_2)) = \frac{F_\epsilon(x\beta_0)F_\nu(x_1\eta_0)}{F_\epsilon(x\beta_0)} = F_\nu(x_1\eta_0).$$

Therefore we could estimate $F_\nu(x_1\eta_0)$ by a non-parametric regression of participating in the incentive program (D) on the eligibility.consideration covariates X_1, for the sub-sample of farmers who adopt the conservation practice. In practice, we will estimate this regression with a Probit regression. In addition, a first testable implication of our model is an exclusion restriction on X_2 in this model.

In addition, we then obtain:

$$\frac{P(1,1|x)}{F_\nu(x_1\eta_0)} = \frac{P(1,0|x)}{1-F_\nu(x_1\eta_0)},$$

so that a second testable implication of our model is the mean-independence restriction:

$$E(\frac{1[(Y,D)=(1,1)]}{F_\nu(x_1\eta_0)} - \frac{1[(Y,D)=(1,0)]}{1-F_\nu(x_1\eta_0)}|X_2) = 0.$$

In practice, we test this restriction of mean-independence with a quadratic regression (but obtain similar results with a linear or cubic regression).

Table ... shows the results of (i) testing the exclusion restriction on X_2 (diesel price for no-till, natural gas price for nutrient management, and productivity index for both practices) in the probit regression of D on X_1 for farmers with $Y=1$, (ii) testing the mean-independence between $\frac{1[(Y,D)=(1,1)]}{F_\nu(x_1\eta_0)} - \frac{1[(Y,D)=(1,0)]}{1-F_\nu(x_1\eta_0)}$ and X_2 with a quadratic regression, using the estimated probabilities from the probit regression to calculate the necessary weights.[4] We see that, while we reject these implications at low levels of significance for no-till practices (for which we estimate a statistically significant treatment effect in the main text), and we reject the mean-independence restriction when no weighting is employed ($E(1[(Y,D)=(1,1)]-1[(Y,D)=(1,0)]|X_2) \neq 0$), we do fail to reject (at any of

[4]We use diesel price or natural gas price and productivity index as the excluded covariate here as these are the most significant excluded covariates in our model of adoption and selection, see Table 1 and the corresponding discussion in the main text.

the commonly used significance levels) the exclusion restriction on X_2 in the probit model and the statistical significance of a quadratic regression of $\frac{1[(Y,D)=(1,1)]}{F_\nu(x_1\eta_0)} - \frac{1[(Y,D)=(1,0)]}{1-F_\nu(x_1\eta_0)}$ on X_2 for nutrient management, for which we do not estimate significant treatment effects in the main text.

This shows that, when using this particular set of testable implications, we do not find evidence against our model or against our finding of no significant treatment effects of EQIP for nutrient management practices.

D Summary Statistics

Table 3: Summary Statistics for Nutrient Management Sample

Variable	Obs	Mean
Treatment and outcome variables		
Adopt and receive subsidy	2,519	0.010
Adopt without cost-share	2,519	0.101
Do not adopt	2,519	0.889
Farmer characteristics		
Farmer age (yrs)	2,519	58.505
Mostly farmer = 1	2,519	0.736
Farm characteristics		
Highly erodible = 1	2,519	0.137
ln(operation acres)	2,519	6.023
Owned field = 1	2,519	0.607
Compliance	2,519	0.035
Productivity index	2,519	0.480
Practice costs		
Natural gas price ($/ 000 ft3)	2,519	4.999
Nutrient management cost ($/ac)	2,519	39.139
Nutrient management EQIP payment ($/ac)	2,519	28.162

Table 4: Summary Statistics for No-till Sample

Variable	Obs	Mean
Treatment and outcome variables		
Adopt and receive subsidy	2,315	0.012
Adopt without cost-share	2,315	0.397
Do not adopt	2,315	0.591
Farmer characteristics		
Farmer age (yrs)	2,315	58.930
Mostly farmer = 1	2,315	0.729
Farm characteristics		
Highly erodible = 1	2,315	0.174
ln(operation acres)	2,315	5.920
Owned field = 1	2,315	0.623
Compliance	2,315	0.264
Productivity index	2,315	0.482
Prices and practice costs		
Diesel price ($/gal)	2,315	2.652
No-till cost ($/ac)	2,315	21.889
No-till EQIP payment ($/ac)	2,315	16.078