Agricultural and Resource Economics Review (2024), **53**, 251–276
doi:10.1017/age.2023.39

RESEARCH ARTICLE

Contract noncompliance in agricultural conservation programs: Panel evidence from Louisiana, USA

Santosh Pathak[1], Hua Wang[2] and Naveen C. Adusumilli[1]

[1]Department of Agricultural Economics and Agribusiness, Louisiana State University (LSU) and LSU Agricultural Center, Baton Rouge, LA, USA and [2]Louisiana Department of Education, Baton Rouge, LA, USA
Corresponding authors: Santosh Pathak; Email: santoshpathak153@gmail.com or Naveen C. Adusumilli; Email: nadusumilli@agcenter.lsu.edu

(Received 19 May 2023; revised 17 November 2023; accepted 26 November 2023; first published online 12 January 2024)

Abstract
Cost-share contracts, offered through working lands programs, are instrumental in addressing environmental externalities from agriculture and generating ecosystem services. However, the persistent trend of noncompliance with cost-share contractual terms has become a problem for funding agencies and policymakers. This paper aims to study noncompliance issues within the US working lands programs using historical county-level panel data (1997–2019) from Louisiana. The results show that noncompliance is attributed more to cancellations than terminations due to flexible provisions within the cancellation option. The significant incentive effect of payment obligations reveals that revisiting payment rates could reduce contract noncompliance and mitigate moral hazard.

Keywords: Contracts; cost-share; CSP; EQIP; moral hazard; noncompliance

JEL Classification: Q15; Q58; D82

Introduction
Cost-share subsidies in working lands programs have been an attractive policy option in abating agricultural impacts on natural resources and achieving environmental conservation goals (Claassen et al., 2008; Lichtenberg, 2019; USDA-ERS, 2023). Working lands programs, such as the Environmental Quality Incentives Program (EQIP) and the Conservation Stewardship Program (CSP), offer cost-share options to encourage the adoption of environment-friendly and sustainable agricultural production practices. The inherent aim of such programs is to incentivize farmers to indirectly improve soil and water quality by altering production practices on private lands. Cost-sharing provision is appealing to farmers as it compensates for the financial load of implementing conservation practices, also known as best management practices (BMPs), that behave like impure public goods. Conservation practices stabilize yield, limit environmental externalities from agriculture,

and provide economic benefits to farmers (Park et al., 2022; Williams et al., 2018); thus, they are being increasingly prioritized through the US Farm Bill.

The 1996 US Farm Bill established working lands programs emphasizing conservation initiatives without halting agricultural production. Since 1997, >$30 billion[1] has been invested through ~0.90 million contracts in 476 million acres of private lands across the country (Figure 1). These investments are mostly geared towards, but not limited to, promoting soil health and plant productivity, overcoming inefficient irrigation water use, terrestrial habitat management for wildlife, addressing feed and forage imbalance, and livestock management. Agricultural cost-share programs utilize federal, state, or local funding pools to provide financial incentives to farmers through conservation contracts. Cost-share contracts are allocated through a competitive selection[2] process based on natural resource concerns in a given area. The cost-share contracting scheme has been instrumental in managing resources and addressing environmental concerns surrounding working lands (Liu et al., 2022). However, programs involving cost-share contracting are not without problems. For instance, breaking contractual obligations leading to noncompliance[3] has become a pressing issue.

Noncompliance occurs when a participating farmer opts out of the contract either through the cancellation or termination option. Working lands programs have been challenged by the rising rate of contract noncompliance over the last two decades, particularly through contract cancellation citing personal, financial, environmental, or other hardships. We presume that a higher cancellation rate maybe associated with the option to withdraw from implementing existing conservation practices without incurring penalties. The cancellation option, unlike termination, offers a strategic advantage, as it does not likely result in assessment of liquidated damages, and points are not deducted in future cost-share applications. The absence of these penalties incentivizes to choose cancellation over termination. Such strategic advantage maximizes farmers' benefits while potentially hindering conservation efforts of the Natural Resource Conservation Service (NRCS), which heavily invests in cost-share contracts. Noncompliance poses additional challenges to agricultural conservation programs by eroding ecosystem services accumulated through a series of investments and efforts over the past 25 years. In addition, the ex-post efficiency of the program is altered through increased public expenditures from contract withdrawal and increased taxpayers' burden to meet environmental goals, thus decreasing social welfare. Since, noncompliance diminishes prospects for private and societal benefits from conservation efforts, overlooking the noncompliance problem over the long term could also exacerbate complications for conservation programs.

Despite the enormity of the challenges posed by contract noncompliance, only a few existing studies explore this topic within the context of US working lands programs. Wallander et al. (2019) studied patterns of dropped practices in EQIP and suggest changes to cost-share rates as one of the possible options to address challenges from unrevealed incentives in the program. However, to our knowledge, causal estimates of the impact of contract payment rate on (non)compliance in working lands programs are not yet available. Similarly, Cattaneo (2003) studied conservation practice withdrawals at the

[1]Real payments in 2022 dollars. The nominal investment is ~$25 billion dollars from 1997-2022.

[2]On average, only one out of three applicants are awarded cost-share contracts. This figure may be even lower for major US agricultural states (https://www.iatp.org/documents/closed-out-how-us-farmers-are-denied-access-conservation-programs).

[3]The noncompliance term we have used here is not related to the failure to meet mandatory compliance requirements under Highly Erodible Land Compliance. Noncompliance here refers to non-completion or the failure to implement conservation practice(s) specified in contract guidelines.

https://doi.org/10.1017/age.2023.39

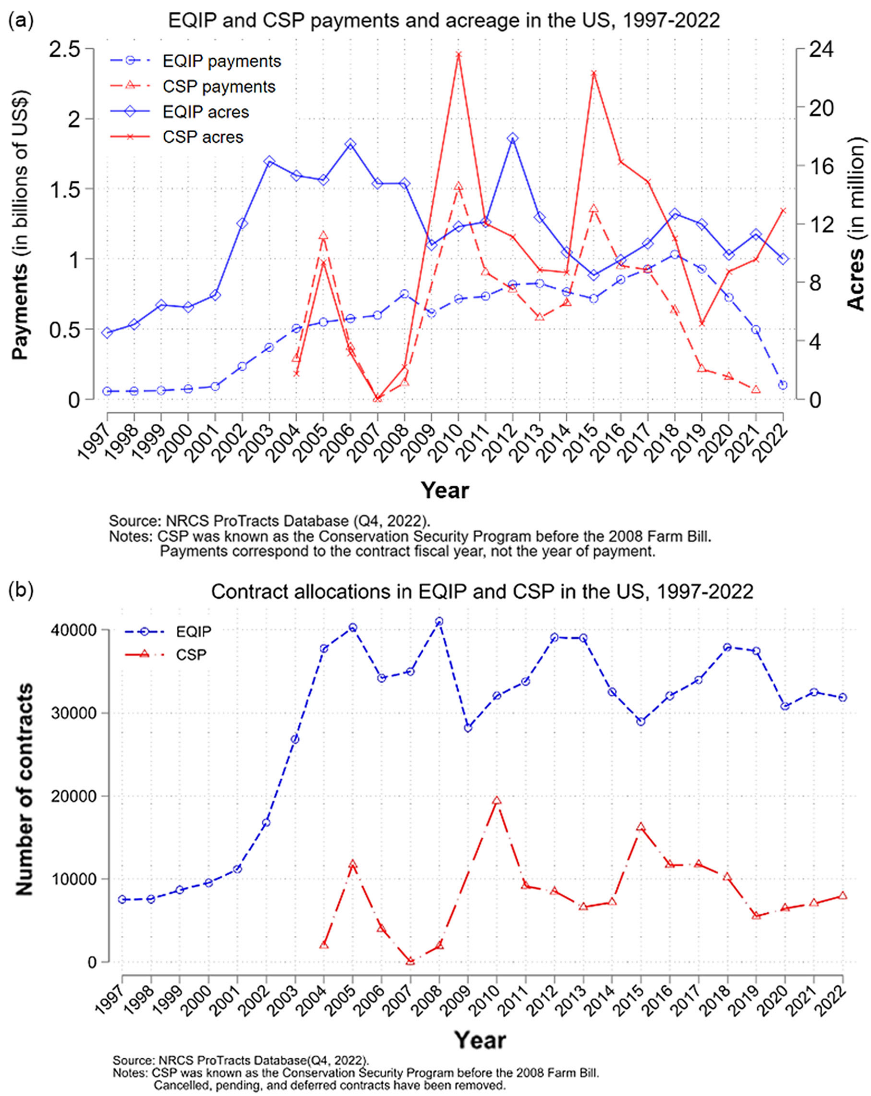

Figure 1. Distribution of (*a*) payments and acreage, and (*b*) contract allocations in Environmental Quality Incentives Program (EQIP) and Conservation Stewardship Program (CSP) in the United States, 1997-2022.

beginning of EQIP and showed how moral hazard creates uncertainty about prospective benefits from the program. However, how moral hazard – a situation in which risk-sharing individuals' private actions negatively alter the probability distribution of the program outcome (Holmström, 1979) – evolved as EQIP and CSP programs matured over time is not much explored empirically. In light of these issues, this study empirically investigates three major research questions: (1) What is the level of noncompliance in cost-share programs? (2) What is the impact of contract payment obligations on the noncompliance rate? (3) Is there any empirical evidence supporting the presence of moral hazard in cost-share programs?

To answer these questions, we first obtained county-level panel data on contract status and payments in EQIP and CSP programs during 1997–2019 in Louisiana and combined it with other secondary data. The southeastern agricultural state, Louisiana, accounts for ~$680 million in investments through >24,000 contracts spanning >6.33 million acres of farmland since 1997 under working lands programs (Figure A1). Second, we use three econometric strategies to draw inferences. We specify a linear fixed effects (FE) model, non-linear fractional outcome model, and spatial model in a panel framework to draw inferences. Our analysis shows that noncompliance costs ~$0.87 million annually to funding agencies in Louisiana. The results indicate that a one percent increase in payment obligations decreases the noncompliance rate by ~0.07 percentage points. Furthermore, we provide empirical evidence of moral hazard through a range of observations, including consistently higher selection of the flexible cancellation option, spatial clustering of noncompliance rates around regions with intensive agricultural operations, and the strategic response of farmers to changing market and environmental conditions after signing contracts. Our findings about the significantly negative effect of payment rates on noncompliance and moral hazard mechanisms are robust across a suite of robustness checks, including Lewbel's instrumental variable method and relative correlation restrictions approaches.

This article adds to the existing literature on contract noncompliance and moral hazard by Ozanne et al. (2001), Cattaneo (2003), Giannakas and Kaplan (2005), Yano and Blandford (2009), Wallander et al. (2019), and Pates and Hendricks (2020). We contribute to three strands of literature. First, to the literature on cost-share contracts and, more broadly, on issues facing working lands programs. Second, we study the magnitude of the incentive effect of payment obligations on the county-level contract noncompliance rate. This is highly relevant as the new Farm Bill, which includes funding for conservation programs as priority areas, is on the horizon. Third, this article demonstrates various sources of moral hazard (e.g., consistently higher preference for cancellation option, adherence during environmental adversities and infringement during farm earnings increment, and spatial clustering of noncompliance) and bolsters theoretical claims about moral hazard within the domain of the US agricultural conservation programs. Our findings provide valuable insights to both funding agencies and policymakers on the reasons underlying the steady noncompliance rate in agricultural conservation programs despite offering greater flexibility for producers by the government to foster ecosystem services generation.

The remainder of the paper is organized as follows. The following section provides an overview of cost-share contracts in working lands programs. Section 3 presents the conceptual framework of the study. Section 4 deals with data and methods. Section 5 presents results and discussion. Section 6 concludes the paper with directions for future research.

Cost-share contracts: an overview

A county[4] consists of several farmers that grow crops or raise livestock and due to their intensive production practices, they partly contribute to nonpoint source pollution. This pollution is widely recognized as a major precursor of soil and water quality impairment around or off-farm(s) (Rabalais et al., 2002; Ribaudo & Shortle, 2019; Del Rossi et al., 2023). Therefore, conservation agency such as NRCS, through its field staff, frequently interacts with farmers regarding various aspects of production practices and their

[4]In Louisiana, a county is referred to as "parish."

implications for environmental quality. The agency also provides farmers with an option to participate in cost-share programs to augment environmental conservation goals without disrupting agricultural production. The agency employs voluntary contracts as a promising alternative to command-and-control regulations for implementing conservation practices such as nutrient management, cover cropping, integrated pest management, residue and tillage management, fencing for livestock, livestock waste storage systems, and alike.

In this study, we presume that the decision to adopt conservation practice with a cost-share contract is subject to the classical principal-agent problem, whereby NRCS is the principal that cannot perfectly observe conservation practice implementation, and the farmer is the agent of the decision. NRCS and farmers write contracts to overcome possible inefficiencies arising from asymmetric information. Such contracts allow farmers to be reimbursed majority (~75%) of the costs incurred in installing or continuing conservation practices.[5] The remaining portion is due, in part, to farmers so that they have some incentives to take care of practices being implemented on their land, potentially contributing to contract compliance. The reimbursement is conditional on some visible and verifiable outcomes that depend on the farmer's effort and random events outside the farmer's control. The mutual payoff from a contract depends on an outcome that is contingent on the agent's commitment. To generate ecosystem services from private lands, NRCS expects farmers to be committed to contractual obligations in a multi-period setting. However, there is variability in expected costs and output during contract implementation across both spatial and temporal dimensions. In addition to the variability in costs and benefits, some intrinsic incentives beyond the contractual obligations motivate farmers to renegotiate or violate contractual terms citing personal, financial, environmental, or other hardships.

Participation in the cost-share program is voluntary and begins at the will of the farmers. Therefore, at the beginning of the contract, all farmers are assumed to be the same in terms of their understanding of the relative benefits of implementing conservation practices on their lands. All farmers enter into cost-share contracts as they are more attracted by the prospective long-run benefits of implementing BMPs on their working lands. However, after they enter into contracts, both market and farm conditions may change. The favorable changes in (non)market factors make the opportunity cost of complying with contractual obligations very high. In other words, the interplay of both financial and non-financial motives (e.g., preferences and risk aversion) affects contractual obligations or compliance (Adusumilli et al., 2020; Pathak et al., 2021; Dean et al., 2023). Thus, noncompliance could be triggered as a part of adaptive management to respond to unexpected circumstances beyond the participant's control or due to unrevealed private benefits to farmers unbeknown to NRCS (Wallander et al., 2019).

Cost-share contracts are naturally incomplete, or can be thought of as incomplete, as both principal and agent cannot foresee all possible contingencies (Hart, 1995). This inherent incompleteness exposes both parties to risks such as unanticipated ex-post costs and unfavorable returns on investments. The incomplete nature of contracts also provides farmers with more flexibility to reassess compliance payoffs when future (non)market conditions drift beyond expectations (Gow et al., 2000). At each point in time, both the NRCS and the farmer in a contractual relationship weigh the costs and benefits of implementing the practice up to a prespecified period. Noncompliance occurs when unanticipated changes in external environments fairly affect the benefit-cost ratio, making contractual breach optimal for one or both parties (Gow & Swinnen, 2001). Contractual

[5]This number can be as high as 90% for beginning or historically underserved farmers.

guidelines minimize information gaps, remove undue rigidity, and encourage both parties to approach desired performance levels. However, breaching or dropping contracts, in any form, surcharges program implementation costs and impedes the environmental conservation goals of the program (Sawadgo & Plastina, 2022). Other challenges that diminish the effectiveness of working lands programs include competing production and conservation systems, difficulty in monitoring, inadequate technical assistance, and contract complexities (Aillery, 2006).

Four things need to be understood regarding program characteristics before the formal analysis: First, there is "exclusivity" and "semi-commitment" in the working lands contracts. This implies that farmers cannot have cost-share contracts with multiple federal agencies at once in a given period. Second, the "Conservation Assessment Ranking Tool (CART)" ranks contracts based on current fiscal year criteria and the applicant's eligibility before beginning a contractual relationship.[6] This mechanism is uniform across contracts. Third, contract participation, implementation, and continuation are voluntary with EQIP and CSP programs. However, a subtle difference to note between these two programs is that EQIP focuses on conservation practice initiation, while CSP is more about the enhancement of existing conservation practice(s) (Czyżewski & Kryszak, 2022). Lastly, terminations and cancellations occur for the whole contract in its entirety and do not apply to specific management practice(s).

Conceptual framework

Our conceptual framework is influenced by the works of Grossman and Hart (1983), Gow et al. (2000), and Peterson et al. (2014). The model includes crop and livestock farmers deciding whether to implement conservation practices on their working lands and a funding agency that encourages conservation practices adoption via cost-share support. Consider two parties (NRCS and farmer) interacting with each other, directly or indirectly, about the possible mutual contractual relationship at some initial date 0. At date 1, the agency makes a contingent promise to farmer n ($n = 1, 2, \ldots, N$) about investment on a shared basis for implementing conservation practice(s) and writes a contract for duration $t \in (0, T]$ with a cost-share rate, $\zeta \in (0, 1)$, which necessitates farmer's approval. The conservation practice implementation is expected to cost $c_{nt} \geq 0$ for farmer n when adopting in time t. This implementation cost, most of which is reimbursable, must be initially borne by the farmer. Farmer n's conservation initiative is expected to provide private benefit π_n. The farmer n accepts a cost-share contract if the present value of expected return (π) by enrolling in contractual obligations – i.e., $\sum_{t=0}^{T} d_t \pi_{nt}$, where $d \in [0, 1)$ is the discount factor – is greater than that without contracts. Contract awarded by NRCS to a farmer with cost-share rate ζ is represented as $(m, \boldsymbol{x})$, where m is the total monetary payment obligations associated with the contract and $\boldsymbol{x}$ is a vector of characteristics of the farmer and of cost-share contract besides payment obligations, such as acreage, farm earnings, exposure to environmental adversities, and alike.

At some date 2, the agency's initial projection about the associated costs and potential benefits are realized by the farmer. The realized costs and benefits depend on the farmers' investment, commitment level, and ex-post realization of perceived uncertainties ex-ante. Based on realized costs and benefits with the implementation of the contract, farmer faces two alternatives: comply or not comply. The expected utility for contract participants can be represented as (Peterson et al., 2014):

$$U_{nt}(m, \boldsymbol{x}) = \max\{\psi m_{nt} - c_{nt}(\boldsymbol{x}), \quad \psi m_{nt} - w_{nt}(\boldsymbol{x})\} \tag{1}$$

[6]CART was known as Application Evaluation and Ranking Tool (AERT) before the 2018 Farm Bill.

https://doi.org/10.1017/age.2023.39

where ψ represents the marginal utility of contract payment obligations. c_{nt} denotes the expected disutility of contract compliance that accounts for practice(s) implementation costs, operational costs, and opportunity costs of income forgone from short-term production losses while obeying contractual terms. Similarly, w_{nt} denotes disutility resulting from the forfeiture of all rights to any additional payments as described in the contract, requirement to return payments previously issued from the contract, reputation costs, or noncompliance penalties such as liquidated damages costs. Until $w_{nt}(\boldsymbol{x}) \geq c_{nt}(\boldsymbol{x})$ in equation (1), farmer complies with contractual terms. However, if $w_{nt}(\boldsymbol{x}) < c_{nt}(\boldsymbol{x})$, farmers become non-compliant. Based on these possible binary choices, the decision rule can be represented as:

$$p_{nt}(m,\ \boldsymbol{x}) = \begin{cases} 1 & \textit{if } w_{nt}(\boldsymbol{x}) \geq c_{nt}(\boldsymbol{x}) \\ 0 & \textit{if } w_{nt}(\boldsymbol{x}) < c_{nt}(\boldsymbol{x}) \end{cases} \tag{2}$$

where $p_{nt} = 1$ and $p_{nt} = 0$ denote compliance and noncompliance, respectively. Farmer chooses the option that provides the highest utility during the contract implementation phase. Farmers' collective choice subsequently determines the county-level (non) compliance rate. Thus, the county-level noncompliance rate is the summation of the number of non-compliant farmers to the total number of farmers receiving cost-share contracts and is calculated as:

$$y_t = 1 - \left[\frac{\sum_{n=1}^{N} p_{nt}(m,\ \boldsymbol{x})}{N}\right] \tag{3}$$

where $y \in [0,\ 1] \subset \mathbb{R}$ is the county-level noncompliance rate.

Data and methods

Data

The dependent variable in this study is the rate of noncompliance. We construct this variable by taking the ratio of the sum of canceled and terminated contracts to the total number of contracts allocated in each county. Both canceled and terminated contracts are considered non-compliant in this study as they do not contribute toward conservation program goals, leading to missed program targets and increased costs. The annual data on contract status aggregated at the county level were obtained from the NRCS Resource Economics, Analysis, and Policy Division for the 1997–2020 funding years for Louisiana. This panel dataset contained information about contract status, acres, obligations, and payments by county across the years. We limit our study to only two working lands programs, EQIP and CSP, which constitute a major share (~96%) of the working lands program spending in Louisiana. Both of these programs are administered by the NRCS under the US Department of Agriculture. The proximity to the Gulf of Mexico, the endpoint for the nation's most important Mississippi River, and a hotspot for the "hypoxic zone," makes Louisiana an ideal state for the study. Figure 2 presents yearly contract allocations under EQIP and CSP programs along with the frequency distribution of contract status since the inception of these programs. A total of 23,531 contracts were awarded in Louisiana from 1997 to 2019, with an average of 980 contracts per year and around 15 contracts per county. The county-wise contract allocations across Louisiana during the study period are mapped in Figure A2, revealing a higher frequency of contract allocations in the Mississippi River and Red River basin in the north, and the Acadiana region in the south of Louisiana.

https://doi.org/10.1017/age.2023.39

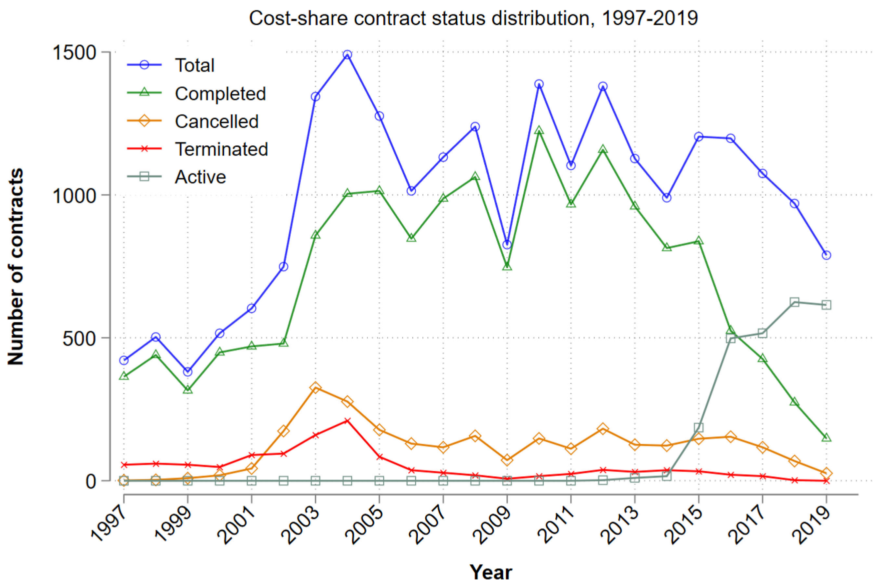

Figure 2. Distribution of cost-share contract allocations and their status during 1997–2019 in Louisiana.

Besides data on the noncompliance rate, payment obligations, and planned acres, additional data were collected for covariates such as farm income and earnings,[7] production expenses, land values, loss ratio, debt-income ratio, heating degree days (HDD), and land retirement payments. We include these covariates in our empirical model because of their likely influence on the county-level noncompliance rate. The county-level farm income, farm earnings, and farm production expenses data were obtained from the Bureau of Economic Analysis (2021) to construct the expenditure-to-income ratio. This ratio is an indication of farmers' relative burden with production expenditure. Data on farmland values were obtained from the USDA National Agricultural Statistics Service (2020). Farmland values are a reflection of land productivity. Data on loss ratio were obtained from the USDA Risk Management Agency Summary of Business (2021). The loss ratio represents the ratio of total indemnity paid to the total premium received at the county level and is an indicator of the impacts of both weather and market-related shocks. County-level debt-to-income ratio data was obtained from the Federal Reserve System (2021), which is an indicator of farm financial health. HDD data, as an indicator of potentially harmful weather and environmental conditions, was obtained from the PRISM Climate Group (2021). Furthermore, data on land retirement payments through the Conservation Reserve Program (CRP) was obtained from the USDA Farm Service Agency (2021). CRP payments indicate the level of concern and priorities for conservation issues in the county (Connor et al., 2021).

Among the 64 counties in Louisiana, we excluded Orleans County before formal analysis because cost-share contract allocations in this county were not common. Moreover, the values of several independent variables for Orleans County were unrealistic. We further removed four additional counties (i.e., Jefferson, Plaquemines, Saint Bernard,

[7]Farm earnings include farm wages and salaries along with farm supplements to wages and salaries, besides farm income.

https://doi.org/10.1017/age.2023.39

and Saint John the Baptist) during the final analysis because they had fewer than 10 county-year observations on the values of the noncompliance rate during 1997–2020. In addition, we did not use data for the funding year 2020 during the final analysis because most of the contracts were marked active, and only three contracts awarded in 2020 were completed as of early 2021.

Model specification and estimation strategy

We estimate the impact of payment obligations on the county-level contract noncompliance rate using the following empirical specification (Cameron & Trivedi, 2005):

$$Non\_com_{it} = \beta ln(Pay\_obg_{it}) + \theta \boldsymbol{x}'_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{4}$$

where Non_com_{it} is the contract noncompliance rate for county i during year t; Pay_obg_{it} is the average payment obligations (in nominal \$/acre); $\boldsymbol{x}$ is the vector of explanatory variables that includes contract acreage, expenditure-to-income ratio, HDD, land values, debt-to-income ratio, loss ratio, and CRP payments; α_i denotes county FE; γ_t denotes time FE; ln represents natural logarithmic transformation; and ε_{it} denotes error term. β and θ are parameters to be estimated.

Given that our dataset is panel-type, we first employ a traditional linear two-way FE model to estimate equation (4). The linear panel model with two-way FE controls for unobserved heterogeneity due to county-specific and year-specific confounders simultaneously. Besides that, we use cluster-robust standard errors that cluster on the county. The use of cluster-robust standard errors is required because the error term might be correlated over time for a given county, thus likely violating the assumption that regression errors are independently and identically distributed (*i.i.d*). Addressing all these possible issues during estimation allows for better identification of the impact of payment obligations and provides robust evidence of associated incentive effect in conservation programs.

Robustness checks with alternative specifications

Despite the promising properties of the FE model in our panel data framework, it may not adequately account for the fractional nature of our dependent variable. The noncompliance rate in our model is a proportion that is bounded between 0 and 1, with both extreme bounds included. This makes our specification in equation (4) non-linear. Therefore, we use the fractional response model developed by Papke and Wooldridge (2008) for panel data and extended by Ramalho et al. (2018) and Wooldridge (2019) for the unbalanced panel. The panel fractional response model that we employ in this study is also known as the correlated random effects (CRE) model and can be specified as (Papke & Wooldridge, 2008):

$$\mathbb{E}(Non\_com_{it} | \boldsymbol{x}_{it},\ \alpha_i) = \Phi(\boldsymbol{x}_{it}\beta + \alpha_i), i = 1, \dots, N \text{ and } t = 1, \dots, T \tag{5}$$

where $\boldsymbol{x}$ is the vector of explanatory variables discussed above, α_i denotes county-specific characteristics, and $\Phi(.)$ is a nonlinear probit link function satisfying $0 \leq \Phi(z) \leq 1$ for all $z \in \mathbb{R}$. The unobserved heterogeneity in equation (5) is modeled as a function of the number of yearly data for each county and the yearly averages of independent variables for each county (Wooldridge, 2019). The average marginal effects are calculated to quantify the effect sizes of independent variables and make values comparable across different models as (Papke & Wooldridge, 2008):

https://doi.org/10.1017/age.2023.39

$$ME_{x_k} = \frac{\delta E(Non\_com_{it}|\boldsymbol{x}_{it}, \alpha_i)}{\delta x_k} = \beta_k \varphi(\boldsymbol{x}_{it}\beta + \alpha_i), \tag{6}$$

where φ represents the standard normal conditional distribution function. The CRE model addresses likely endogeneity from unobserved heterogeneity in the model specification and exploits variation in contract payment obligations and contract acreage while also accounting for the non-linearity of the dependent variable using the quasi-maximum likelihood technique for estimation (Wooldridge, 2019).

Besides the linear FE model and non-linear CRE model, we also extend our analysis using the spatial panel data model because of the possibility of spatial autocorrelation in noncompliance rates across different regions within the study area. Spatial autocorrelation in our case can be due in part to the spatial data aggregation process and spatial heterogeneity. The spatial panel data model accounts for the possible dependence of observations from similar geographical regions, thus providing more credibility to the empirical estimates. To this end, we applied the spatial autoregression model (SAR), spatial error model (SEM), and spatial autoregressive combined (SAC) model to estimate the influence of different variables on the contract noncompliance rate. SAR, often known as the spatial lag model, uses a spatially lagged dependent variable as a regressor to account for the neighborhood effect while SEM incorporates spatial dependence in the disturbance process by splitting error into random error and spatially structured error (Anselin, 1988). SAC is also known as the Kelejian-Prucha model and is an extension of the SAR model by incorporating spatially autocorrelated error term besides spatially lagged dependent variable. A general specification for spatial panel model with spatial and time-fixed effects is given by (Belotti et al., 2017; LeSage & Pace, 2009):

$$y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{jt} + \sum_{k=1}^{K} x_{itk}\beta_{\mathbf{k}} + \sum_{k=1}^{K} \sum_{j=1}^{n} w_{ij} x_{jtk} \theta_{\mathbf{k}} + \mu_i + \gamma_t + \nu_{it} \tag{7}$$

$$\nu_{it} = \lambda \sum_{j=1}^{n} m_{ij} \nu_{jt} + \varepsilon_{it}, \quad i = 1, \ldots, \text{and}\, t = 1, \ldots, T. \tag{8}$$

where y denotes the dependent variable, x represents independent variable, k indexes regressors, i indexes county $(i \neq j)$, ρ is a spatial lag coefficient, β represents the regression coefficient, μ and γ are fixed-effects parameters, t indexes time, w_{ij} and m_{ij} are a part of spatial weighting matrix $\boldsymbol{W}$ and denotes spatial weight related to units i and j, λ is a spatial error coefficient, ν is a spatially structured error term, ε is a random error term, $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$, and $\nu_{it} \sim N(0, \sigma_\nu^2)$. In equations (7) and (8), $\lambda = 0$ and $\theta = 0$ for SAR. In the case of SEM, $\rho = 0$ and $\theta = 0$ in equation (6). If SAC, $\theta = 0$.

All three spatial models are estimated using the quasi-maximum likelihood approach.[8] Before model estimation, we constructed a 59×59 spatial weighting matrix ($\boldsymbol{W}$) for 23 years using the Queen contiguity case of order 1. The Queen contiguity matrix considers neighborhood relationships among spatial units that share either edges or corners. The spatial weighting matrix was later row standardized. Unlike non-spatial panel regression, spatial panel regression cannot be easily implemented with unbalanced data. We, therefore, employ the multiple imputation method to deal with missing values of dependent variables under consideration.[9]

[8] We used *xsmle* Stata command of Belotti et al. (2017) for estimating spatial models.

[9] 8.92% observations were missing for dependent variables under consideration.

https://doi.org/10.1017/age.2023.39

Robustness checks with alternative estimation procedures

Although the two-way FE model accounts for endogeneity arising from county-specific and time-specific unobservables, there is a possibility that residual endogeneity owing to time- and county-varying unobservables may influence both contract payment obligations and noncompliance rate, thus leading to biased estimates. The common solution to this problem is to use instrumental variables (IVs) that satisfy exclusion restrictions. However, to our knowledge, there is no external IV that satisfies exclusion restrictions by being strongly correlated with the potentially endogenous regressor but uncorrelated with the dependent variable. To overcome this challenge, Lewbel (2012) provides an external instrument-free approach, often known as the Lewbel moment-based IV estimator. The Lewbel IV estimator leverages heteroskedasticity in the error terms for the identification of coefficients in models with mismeasured or endogenous regressors. For a potentially mismeasured main regressor in equation (4), the first-stage regression according to Lewbel (2012) is expressed as:

$$Pay\_Obg_{it} = \xi \boldsymbol{X}_{it} + v_{it} \tag{9}$$

If the above equation (9) fulfills two assumptions, i.e., (*i*) $Cov\left(\boldsymbol{X}_{it},\ v_{it}^2\right) \neq 0$ and (*ii*) $Cov(\boldsymbol{X}_{it},\ \varepsilon_{it} v_{it}) = 0$, then $\left(\boldsymbol{X}_{it} - \bar{\boldsymbol{X}}\right)\hat{v}_{it}$ could be used as a valid IV (Lewbel, 2012). Condition (*i*) holds if the error term is heteroskedastic in equation (9). The Breusch-Pagan test rejects the null hypothesis that errors are homoscedastic for our data ($\chi^2_{(1)} = 55.96; p < 0.001$), thus satisfying the condition (*i*). Following Baum and Lewbel (2019), we use the Hansen *J* test (also known as the overidentification test) to check if the above condition (*ii*) holds. The overidentification test fails to reject the null that our IVs are valid (Hansen *J* statistic = 0.121; *p*-value = 0.728). The fulfillment of two necessary conditions for validity of heteroskedasticity-based instruments insinuates that the Lewbel IV method is suitable for our dataset.

We also use recently developed relative correlation restrictions (RCR) approach by Krauth (2016) to see how deviations from exogeneity assumption might influence our estimates. The RCR approach provides plausible bounds on the causal effect with a likely endogenous regressor when IVs satisfying traditional exclusion restrictions are absent. In this study, the RCR method provides bounds on the effect of payment obligations on the county-level noncompliance rate based on a relative correlation parameter (λ). The parameter λ depicts the correlation between the main regressor (i.e., payment obligations) and the unobservable error term (ε_{it}) relative to the correlation between payment obligations (Pay_Obg_{it}) and the set of controls ($\boldsymbol{X}_{it}$) (Krauth, 2016). The RCR model assumes that

$$corr(Pay\_Obg_{it},\ \varepsilon_{it}) = \lambda corr(Pay\_Obg_{it},\ \theta \boldsymbol{X}_{it} + \alpha_i + \ \gamma_t + \varepsilon_{it}), \tag{10}$$

where $\lambda \in [\lambda_L,\ \lambda_H]$. The linear specification in equation (4) is a special case in which $\lambda_L = \ \lambda_H = 0$ and $corr(Pay\_Obg_{it},\ \varepsilon_{it}) = 0$. If $\lambda = 1$, then the unmeasurable correlation of payment obligations with unobservables is equal (both in sign and magnitude) to its measurable correlation with the controls.

According to Krauth (2016), $[\lambda_L,\ \lambda_H] = [0,\ 1]$ can be used as a reasonable benchmark to check the robustness of estimates from the linear 2-way FE model. If the estimated bounds of the effect of payment obligations on noncompliance rate are statistically significant and have the same sign as the 2-way FE model for a range of λ between zero and λ_H, then the results are invalidated only in the presence of a substantial amount of residual endogeneity (Chen et al., 2022).

The Lewbel IV and RCR approaches may not fully address the residual endogeneity problem; however, these alternative estimation strategies enhance the credibility of our findings if coefficient estimates from these approaches are consistent with those from the linear FE model.

Table 1. Descriptive statistics of variables

Variable	Mean	SD
Noncompliance rate	0.21	0.24
Cancellation rate	0.15	0.21
Termination rate	0.06	0.14
Payment obligations ($/acre)	183.15	1584.87
Contract acres	254.09	306.50
Loss ratio	0.71	0.98
Land value ($/acre)	2434.01	1122.17
Farm earnings ($)	11818.40	14399.22
Expenditure–income ratio	1.02	0.31
Heating degree days (>32 °C)	36.27	24.44
Debt-income ratio	1.55	0.67
CRP payment ($/acre)	33.03	28.47

Note: SD denotes standard deviation. CRP denotes Conservation Reserve Program. Loss ratio is the ratio of indemnity paid to the amount of premium received. Farm earnings include farm wages and salaries along with farm supplements to wages and salaries, besides farm income. All the values in the table are annual county-level averages for Louisiana during contract year 1997–2019.

Results and discussion

Descriptive results

The average noncompliance rate in Louisiana is 21% (Table 1). The standard deviation of the noncompliance rate is 24% and appears higher than the mean implying that noncompliance varied significantly across counties and over time. This may be due to the differential impact of climatic and market factors during the contract period across Louisiana. The noncompliance rate here is slightly larger than the 14% reported by Wallander et al. (2019) for conservation practices at the national level. The non-compliant acres account for 19.7% (i.e., 742,328 acres) of total cost-share acres. Noncompliance resulted in a sunken cost of roughly ~$0.87 million each year to funding agencies in Louisiana. The social cost might be even higher. The substantial cost of noncompliance is a useful proxy to gauge program efficiency level, or lack thereof, on working lands. Furthermore, disaggregation of the components of noncompliance shows that the average contract cancellation rate (15%) is approximately three times higher than the termination rate (~6%). Figure 3 also underscores consistently higher cancellation trends than termination for most parts of the working lands program history, and naturally gives rise to a question – why cancellations are higher than terminations?

During the 1996 Farm Bill period (1996–2002), noncompliance was attributed more to the termination than cancellation phenomenon; however, that trend reversed with the 2002 Farm Bill (Figure 3). The higher termination rate at the beginning of the working lands program may be due to the convex learning curve of farmers where they were not adequately familiar with the consequences of their adverse actions including assessment of liquidated damages for cost recovery by the NRCS following contract termination. The 2002 Farm Bill placed more priority on working lands than land retirement with increased

https://doi.org/10.1017/age.2023.39

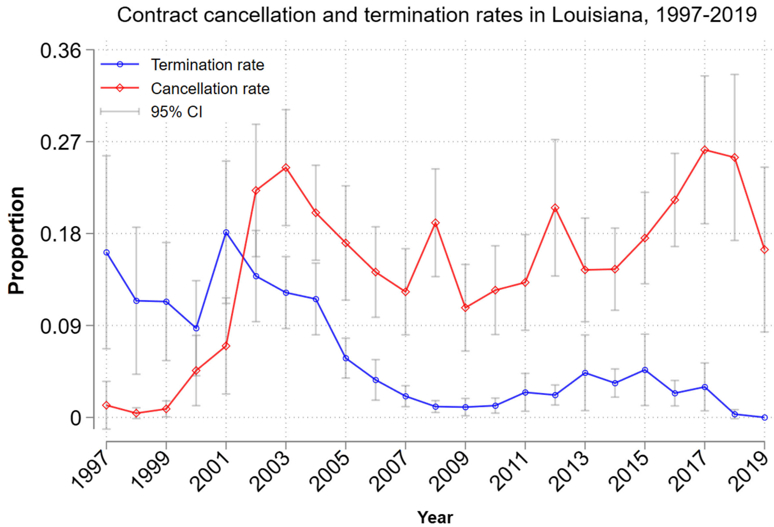

Figure 3. Heterogeneity of termination and cancellation rates during 1997–2019 in Louisiana.

fundings, allowed more flexibility by introducing shorter contracts, and also increased contract payment limitations (Cattaneo, 2003). These changes made it more likely for farmers to secure additional dollars from the program. In addition, the cancellation option is somewhat flexible as it is termed a mutual agreement between the NRCS and the contract participants to end the contract for reasons beyond the participants' control.[10] Cancellations are not considered adverse actions and do not count against participants in future program participation. Moreover, with cancellations liquidated damages costs are not assessed, previously issued payments need not be returned, and only rights to remaining future payments are forfeited. Such provision places canceling farmers in a strategic advantage without any bearings on future program eligibility while also avoiding penalties.

Unlike cancellations, terminations are when NRCS unilaterally ends the contractual agreement due to breaching of the contract terms and conditions by the farmer. Since termination is considered an adverse action, participants may have to pay liquidated damages or return payments previously issued from the contract. NRCS in Louisiana deducts points from applicants' screening and ranking if they have had a contract terminated within the past 3 years. While this does not prevent participants with terminations from applying or potentially receiving another contract, it does place them in a "low" priority category and could reduce their chance of funding for the next 3 years.[11] These provisions in contract guidelines provide space for unverifiable actions and foster moral hazard favoring farmers who can identify reasons to proceed with the cancellation.

Another important observation indicating moral hazard is a negative association between average farm income level and compliance rate, especially after the 2002 Farm Bill (Figure 4). This resembles "opportunistic adoption" (Pannell & Claassen, 2020) and indicates that farmers may be participating in cost-share programs more as a safety net to

[10]See "Conservation Program Contracting" manual: https://directives.sc.egov.usda.gov/OpenNonWebContent.aspx?content=40459.wba. The reasons to end the contract could be related to land ownership, natural disasters, environmental and archaeological concerns, or economic and personal hardships.

[11]We thank NRCS Louisiana officials for providing us with the information about this provision.

https://doi.org/10.1017/age.2023.39

Figure 4. Distribution of compliance, noncompliance, cancellation, and termination rates in working lands programs and farm income in Louisiana during 1997–2019. Overall noncompliance rate is the summation of cancellation and termination rates.

their farm income level than out of concern for environmental conservation. This might also be due to farmers being cash-strapped by implementing conservation practices because there is some time lag in reimbursement of incurred investments. Other reasons for noncompliance may be due to the expensiveness, complexity, and potential risks about expected benefits with some conservation practices whose benefits accrue mostly beyond farms (Baylis et al., 2022). The intention to be non-compliant may also be triggered by time discounting (present bias) and non-aligning expectations regarding productivity, costs, and returns with ground reality after conservation adoption (Duquette et al., 2012; Trujillo-Barrera et al., 2016). Breaching contracts during good times and complying with them during bad times could hinder the goals of conservation programs with significant costs involved and merely any environmental benefits. This further indicates that cost-share contract guidelines necessitate revisiting to address the influence of aggregate farm income on compliance rate and to engender environmental public goods.

Regarding payment levels, the mean (median) nominal payment obligations per contract and per acre in Louisiana are ~$19,880 (~$10,368) and $183.15 ($76.67), respectively (Figure A3). We find a difference in average obligations per acre for compliant and non-compliant contracts by >45% (Figure A4). The mean (median) obligations per acre for completed, canceled, and terminated acres are $246.21 ($85.29), $151.23 ($34.82), and $105.08 ($24.63), respectively. Similarly, the average acreage under contract is 254 acres, with the median being 152 acres. This is almost ~50% of the average farm size in Louisiana as per the 2017 Census of Agriculture. This is an indication that program-participating farmers are enrolling almost half of their working lands in conservation activities. However, there exists a discrepancy in the median acres in both compliant and non-compliant categories (Figure A4). The median acres under completed contracts are 137 acres, while that for canceled and terminated contracts are 100 acres and 101 acres, respectively, which insinuates that contracts enrolling larger acres are the ones that reach completion. McWherter et al. (2022) also report a positive relationship between contract acres and compliance level. This may be due to the higher private benefits and higher

https://doi.org/10.1017/age.2023.39

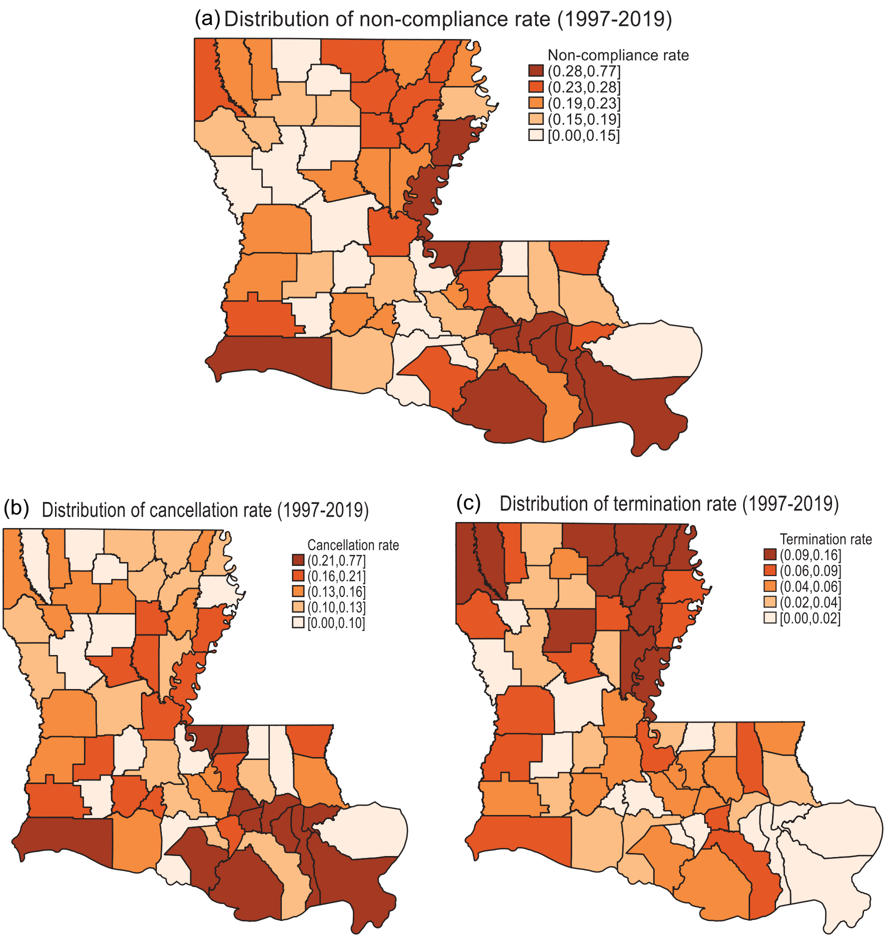

Figure 5. Spatial distribution of *(a)* overall noncompliance, *(b)* cancellation, and *(c)* termination rates in cost-share programs in Louisiana.

liability threats with a bigger contract size, thus providing a higher incentive to be in the program. Another incentive is that conservation practices minimize variable input use in the long run (Delgado et al., 2011), which is critical to improving farm income prevailing resource-intensive production practices. Furthermore, larger contracts mostly emanate from larger farms that are mostly family-run, corporately organized, and might possess intergenerational motives (Featherstone & Goodwin, 1993) to comply with contractual obligations besides long-term profitability and cost-share reimbursements from the government. On the other hand, liability threats are less for smaller contracts allowing farmers to easily sway between (non)compliance choices and exert efforts based on available information set about costs and benefits.

Furthermore, we also found spatial clusters for cancellation and termination rates (Figure 5). Panels (*b*) and (*c*) of Figure 5 show that cancellation is mostly prevalent in the state's rice- and sugarcane-dominant southern regions, whereas termination is widespread in the cotton- and soybean-dominant northern regions. In general, noncompliance seems

https://doi.org/10.1017/age.2023.39

to be clustered around the Mississippi River basin and the Red River basin. A few reasons might have influenced this spatial cluster formation. First, the Mississippi River alluvial plain and the Red River basin predominantly comprise irrigated acres – mostly soybeans, corn, and cotton. Increasing acreage allocation for these crops around the major river basins is to maximize profit. This means farmers always weigh several options that increase their profit level, which is related to being (non)compliant with cost-share contracts awarded to them. Second, part-owners and tenant farmers operate ~32% of farms and cultivate ~68% of the acres in Louisiana. Initially, they have a positive outlook on the prospects of conservation practices because of the likely changes in input usage and profit margins from implementing BMPs. However, it is challenging for them to achieve conflicting dual objectives of short-run profit maximization and generation of public goods within a limited timeframe. The spatial clusters reveal compelling evidence of peer effects in contract noncompliance. Part-owners collectively use contracts as a buffer to their income and inefficiently give up contracts. This represents another moral hazard mechanism, supplementing our earlier findings from Figure 3 about the strategic behavior of farmers in cost-share programs. Spatial clustering due to moral hazard in major agricultural regions also raises regulatory challenges through strict monitoring or penalties.

Econometric results

The parameter estimates obtained from the linear panel model with FE, panel fractional response model (CRE), and SAR model are presented in Table 2. We provide separate results for overall noncompliance, cancellation, and termination rates in Table 2 to examine whether the effects of covariates are uniform or varying for canceled and terminated contracts. The results show that payment obligations are an important determinant of contract compliance. Based on estimates from the linear FE model, a one percent increase in contract obligations level reduces the overall noncompliance rate by ~0.07 percentage points at the county level. The incentive effect of payment obligations from alternative specifications like CRE and SAR models also appears positive and almost equivalent (~0.07) to that from the linear FE model. Moreover, both noncompliance categories, cancellation and termination, show significant incentive effects. The results are consistent with findings by Benítez et al. (2006), Gramig and Widmar (2018), and Park et al. (2022) that increasing monetary incentives could motivate farmers to remain in cost-share programs.

To aid in comprehension of the magnitude of the incentive effect of payment obligations, we performed a simple calculation using the data in hand. The available data from NRCS shows that total noncompliance amounts to ~\$20 million in Louisiana during the study period. An increase in payment obligations per contract by one percent would equate to ~\$0.2 million. Similarly, there were 3,878 non-compliant contracts during 1997–2019. Hence, based on our estimated effect of payment from the FE model, a one percent increase in payment obligations per contract would lead to the compliance of an additional 272 contracts (i.e., $3878 \times 0.07 = 271.46$) that roughly implements conservation practice in ~69,000 acres in Louisiana, generating remarkable off-farm and on-farm benefits. These numbers provide an inkling that the incentive effect of payment obligations to reduce contract noncompliance is substantial and economically meaningful. Further analysis of the incentive effect by separating EQIP and CSP contracts shows that the marginal effect of payment obligations appears almost similar in EQIP (~0.06) and CSP (~0.05) programs (Table A1). Despite this significant ballpark figure, it is worth noting that the magnitude of

https://doi.org/10.1017/age.2023.39

https://doi.org/10.1017/age.2023.39

Table 2. Main results: Estimated coefficients from linear fixed effects, fractional regression, and spatial models with two-way fixed effects

	Overall noncompliance rate			Cancellation rate			Termination rate		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Variables	Linear	CRE[†]	SAR	Linear	CRE[†]	SAR	Linear	CRE[†]	SAR
ln(Payment obligations ($/acre))	−0.073***	−0.074***	−0.070***	−0.054***	−0.039**	−0.052***	−0.019***	−0.011***	−0.018***
	(0.004)	(0.008)	(0.004)	(0.006)	(0.004)	(0.006)	(0.007)	(0.003)	(0.006)
ln(Contract acres)	−0.051***	−0.059***	−0.041***	−0.019	−0.009	−0.011	−0.032***	−0.022***	−0.029***
	(0.009)	(0.010)	(0.008)	(0.011)	(0.012)	(0.010)	(0.012)	(0.007)	(0.010)
Loss ratio	−0.003	−0.003	−0.006	0.002	0.002	−0.001	−0.004	−0.004	−0.005
	(0.006)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
ln(Land value ($/acre))	−0.001	−0.002	0.031	0.100**	0.089*	0.105**	−0.101**	−0.046	−0.068**
	(0.044)	(0.049)	(0.040)	(0.050)	(0.050)	(0.045)	(0.040)	(0.044)	(0.029)
ln(Farm earnings ($))	0.012	0.008	0.009	0.009	0.009	0.002	0.004	0.004	0.007*
	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)	(0.008)	(0.008)	(0.007)	(0.004)
Expenditure-income ratio	0.065	0.066*	0.017	0.055	0.077	−0.004	0.010	0.009	0.025
	(0.043)	(0.038)	(0.047)	(0.045)	(0.048)	(0.039)	(0.039)	(0.030)	(0.016)
ln(Heating degree days (>32 °C))	−0.048*	−0.045*	−0.047*	−0.023	−0.015	−0.028	−0.025	−0.023	−0.019
	(0.026)	(0.024)	(0.025)	(0.028)	(0.023)	(0.026)	(0.018)	(0.014)	(0.018)
Debt-income ratio	0.028	0.016	0.033	0.023	0.017	0.032	0.005	0.006	0.001
	(0.030)	(0.027)	(0.029)	(0.022)	(0.020)	(0.021)	(0.021)	(0.016)	(0.019)

(*Continued*)

Table 2. (*Continued*)

	Overall noncompliance rate			Cancellation rate			Termination rate		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Variables	Linear	CRE†	SAR	Linear	CRE†	SAR	Linear	CRE†	SAR
ln(CRP payment ($/acre))	0.007**	0.007**	0.005**	0.003	0.002	0.001	0.004***	0.003**	0.003***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ρ	–	–	0.044	–	–	−0.020	–	–	0.094*
			(0.041)			(0.046)			(0.056)
R^2	0.42	–	–	0.39	–	–	0.29	–	–
p-value	0.000		0.000	0.000		0.000	0.006		0.000
No. of counties	59	59	59	59	59	59	59	59	59
N	1139	1139	1357	1139	1139	1357	1139	1139	1357

Note: Cluster-robust standard errors are in parentheses. Overall noncompliance rate is the summation of cancellation and termination rates. CRE = Correlated Random Effect; CRP = Conservation Reserve Program; SAR = Spatial Auto Regression. *ln* = Natural logarithm. Loss ratio is the ratio of indemnity paid to the premium collected. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
† The estimated average marginal effects are reported from the CRE model instead of actual coefficient estimates to make values comparable across columns.

the payment effect needs to be further investigated, especially for CSP contracts due to results coming from a relatively smaller number of observations.

Besides payment obligations, contract acreage also exhibits a significantly negative effect on the contract noncompliance rate. The negative effect of payment obligations is consistent across both CRE and spatial models. This result suggests that adjustments in contract size, both in terms of payments and acreage, during allocations could likely generate additional ecosystem services through a reduced noncompliance rate. Furthermore, we are interested in examining whether the common reasons cited in non-compliant contracts (e.g., environmental calamities, unforeseen expenses, and debts) hold true, at least at the county level. We find a consistent and significantly negative influence of HDD on the noncompliance rate. The negative influence of HDD is intuitive because HDD is an indication of climate adversities, and conservation practices have the potential to promote resilience under extreme weather conditions (Bowles et al., 2020; Nouri et al., 2021). We also find that farm earnings, expenditure-income ratio, and debt-income ratio show a consistently positive association with the overall noncompliance rate. The influence of variables other than contract payment and associated production expenses suggests that producers respond differently to favorable (e.g., increase in earnings) and unfavorable (e.g., increase in loss ratio) environments, prioritizing individual interests rather than fostering goals of cost-share contracts (e.g., production sustainability and environmental conservation). The results in Table 2 show that market and environmental conditions duly affect contract noncompliance and alter program outcomes. The existence of moral hazard and the commonality of noncompliance is intuitive during higher farm earnings or favorable environmental conditions as they increase the opportunity costs of compliance. Furthermore, the consistent influence of a suite of factors besides contract size indicates that several incentives exist for contract participants to tailor (non)compliance decisions for increasing private benefits rather than generating ecosystem services. Wallander et al. (2019) note that several contract modifications occur in cost-share programs for reasons including, but not limited to, natural disasters or severe illness; however, the actual reasons remain unclear. Such a trend also insinuates that some intrinsic motivations might be incentivizing farmers to act strategically. NRCS serves as a liaison to mitigate agricultural impacts on natural resources and expects program participants to fulfill contract terms to generate ecosystem services. However, when farmers act in their interest by complying more during unfavorable times and remaining non-compliant during favorable times, it hinders program goals. Such hidden incentives in cost-share programs are a significant concern for funding agencies and policymakers, as they can undermine program efficiency.

We further explored if the frequency of contract allocations was higher in areas at risk of being affected by weather-related events and random market fluctuations. Interestingly, we find that ~48% of the contracts were from higher loss-risk[12] areas, which implies that farmers tend to enroll more acres if they have a history of weather or market-related losses, evidenced by a positive and significant pairwise correlation ($\rho = 0.069$, p-value $= 0.009$) (Figure A5). Moreover, the negative association between loss ratio and noncompliance in Table 2 implies that farmers are risk-averse and counties having higher loss ratios (characterized by high indemnity payment levels) are less prone to noncompliance. This serves as another piece of evidence that the agent's objective of profit maximization does not align well with the principal's goal of environmental conservation. When the objectives

[12]The loss-risk is calculated as the average of the ratio of county-level loss-ratio to state-level measure preceding 10-years following Goodwin (1993). An empirical analysis of the demand for multiple peril crop insurance. *American Journal of Agricultural Economics*, *75*(2), 425–434. https://doi.org/10.2307/1242927.

of contracting parties do not match with each other, achieving program targets will always remain a distant goal. Furthermore, ensuring adequate environmental stewardship is challenging if such effects are not accounted for during the implementation of cost-share programs. This is because cost-share payments are mostly allocated based on potential losses of soil and water quality in a particular area, and reimbursements are action-based rather than results-based, thus giving rise to moral hazard (Zabel & Holm-Müller, 2008).

Robustness checks

To provide validity to the results presented in Table 2, we conducted a series of robustness checks utilizing the 3-way FE model, narrowly defined variables,[13] 2-year and 3-year moving average values (Table A2), and alternative forms of spatial panel models such as SEM and SAC models (Table A3). Our main results regarding the significant and negative influence of payment obligations and contract acreage on contract noncompliance are consistent in all alternative specifications. Moreover, the results from alternative specifications also show that there is an uneven influence of independent variables (e.g., HDD, CRP payment) in the cancellation and termination of contracts at the county level. This observation further strengthens previous claims of hidden incentives in cost-share programs. Due to noncompliance augmented by moral hazard, not only is the provisioning of environmental goods hampered, but accumulated ecosystem services are also wiped out. It is therefore necessary for funding agencies to use indicators such as farm earnings, expenditure-income ratio, HDD, loss ratio, debt-income ratio, and similar others to predict the extent of noncompliance at a regional level. Such predictions could be further used to assess the evolving costs and benefits of programs, thereby helping reevaluate contract guidelines to mitigate moral hazard and achieve the targeted goals of environmental conservation. With a caveat that there could be selection bias due to the omission of four counties having <10 observations in the panel, we re-ran our models without removing any observations from 63 counties in Louisiana. The above results are still consistent in Table A4 and reveal that selection bias is not likely to be an issue in our analysis.

Furthermore, we use additional sets of robustness checks to assess the sensitivity of the results due to potential endogeneity or mismeasured regressors employing Lewbel IV and RCR estimation strategies. The results from the Lewbel IV model show that payment obligations still have a negative and significant effect on the noncompliance rate (Table 3). Moreover, the magnitude of the effect of payment obligations from the Lewbel IV model, i.e., −0.078, closely aligns with that obtained from the linear FE model.

The robustness check results obtained using the RCR approach are presented in Table 4. If the payment obligation is no more correlated with unobservables than it is with the controls, a one percent increase in payment obligations leads to a reduction in the noncompliance rate by 0.07 to 0.16 percentage points. The estimated bounds of the effect of payment obligations in Table 4, with all control variables included, are fairly narrow and still significantly negative suggesting that results obtained using the two-way FE are robust to both moderate and

[13]11.5% of the total cost-share contracts allocated during 1997–2019 were categorized as “active” as of May 2021. Since contracts allocated as early as 2014 and later were active in our dataset, we subset our dataset for the year <2014 during which almost all contracts have been either marked as completed, canceled, or terminated. This was necessary because exclusion of active contracts might influence the model coefficients.

https://doi.org/10.1017/age.2023.39

Table 3. Robustness check: Lewbel moment-based instrumental variable (IV) estimation

Variables	Coefficients
ln(Payment obligations ($/acre))	−0.078** (0.036)
ln(Contract acres)	−0.037*** (0.013)
Loss ratio	−0.002 (0.005)
ln(Land value ($/acre))	−0.001 (0.056)
ln(Farm earnings ($))	0.001 (0.010)
Expenditure-income ratio	0.057 (0.049)
ln(Heating degree days (>32 °C))	−0.065*** (0.010)
Debt-income ratio	0.066*** (0.023)
ln(CRP payment ($/acre))	0.005** (0.003)
R^2	0.29
Cragg-Donald *F* statistic	7.649
Hansen *J* statistics (*p*-value)	0.73
p-value	0.000
N	1051

Note: The dependent variable is noncompliance rate. County fixed effects and time trends are included in the model but not reported for brevity. FE = Fixed effects; *ln* = Natural logarithm; CRP = Conservation Reserve Program. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

substantial departure from exogeneity.[14] Our main results remain robust across a series of robustness checks across different specifications and estimation procedures, thereby providing strong credibility to the causal impact of payment obligations.

The significant incentive effect of payment obligations indicates that increasing the contract payment rate could effectively mitigate both noncompliance and moral hazard. The presence of moral hazard calls forth for the introduction of additional incentive systems that could offset opportunity costs of compliance such as compliance rewards (Yano & Blandford, 2009) and conservation credit policy (Langpap & Wu, 2017) or nudges like empathy nudges (Czap et al., 2019) and green nudges (Carlsson et al., 2021) or revisiting existing flexible guidelines for contract participants choosing a cancellation option. As previously mentioned, combating moral hazard should involve considering changes in aggregate farm income in a way that encourages farmers to utilize cost-share incentives not only for private benefits but also to generate ecosystem services – a primary

[14]The moderate departure from exogeneity occurs when $\lambda \sim 0.5$ and substantial departure occurs if $\lambda \geq 1$ (Krauth, 2016).

https://doi.org/10.1017/age.2023.39

Table 4. Robustness check: Estimated bounds from relative correlation restrictions (RCR) estimation approach

Relative correlation restriction (λ)	Bounds on the effect of payment obligations $[\hat{\beta}_L(\lambda),\ \hat{\beta}_H(\lambda)]$	95% CI
$\lambda = 0$	−0.070	(−0.078, −0.063)
$0 \le \lambda \le 0.1$	[−0.077, −0.070] ***	(−0.085, −0.063)
$0 \le \lambda \le 0.2$	[−0.083, −0.070] ***	(−0.095, −0.063)
$0 \le \lambda \le 0.3$	[−0.091, −0.070] ***	(−0.106, −0.063)
$0 \le \lambda \le 0.4$	[−0.098, −0.070] ***	(−0.119, −0.063)
$0 \le \lambda \le 0.5$	[−0.107, −0.070] ***	(−0.133, −0.063)
$0 \le \lambda \le 1$	[−0.164, −0.070] ***	(−0.244, −0.063)
$\hat{\lambda}^{\infty}$	1.570	
$\hat{\lambda}(0)$	3.476	
Minimum λ for which bounds include zero	1.570	

Note: The dependent variable is noncompliance rate. $\lambda = 0$ denotes linear fixed effects model point estimate. Bounds for the true effect of the main regressor (i.e., payment obligations) are reported in square brackets. $\hat{\beta}_L$ and $\hat{\beta}_H$ denote lower and upper bounds of the estimated parameter. The estimated bounds are obtained using all control variables in the model. In total, 95% cluster-robust confidence intervals (CI) are reported in parentheses. *** denotes significance at 1% level.

focus of working lands programs. In addition, adopting the "fail-fast" approach during program planning and implementation could enhance overall program processes, fostering both agricultural sustainability and environmental quality (Wardropper et al., 2022).

There are a few limitations that might restrict the generalization of findings from this study. The aggregation of the data at the county level could have obscured contract-level behavior. Despite the novelty of this study, results are confined to only one state because data was available to us only for Louisiana. Nevertheless, the framework of this article can be extended to different regions of the US to enhance its validity and investigate the presence of regional heterogeneity in incentive effects and moral hazard, if any. In addition, we conduct this analysis by combining data on both EQIP and CSP contracts and assuming that they are similar. However, some differences exist between these two programs; EQIP emphasizes practice implementation in a narrow time frame (<5 years), while CSP encourages practice continuation over a longer time horizon (>5 years). We use average obligations per acre when comparing between contracts; however, EQIP and CSP contracts encompass both one-time discrete capital projects (e.g., fencing, irrigation wells, roads) not measured in acres and multi-year practices (e.g., grazing and cover crops) measured in acres. Furthermore, moral hazard claims could be strengthened by comparing farmers' stated reasons for noncompliance in administrative data with overarching market, financial, and environment trends. This analysis helps determine whether environmental challenges or market and financial issues primarily drive noncompliance. If environmental challenges outweigh others, moral hazard claims may not hold. Regarding unobserved and uncontrolled variables, we believe that the consistency of FE model estimates with the results from Lewbel IV and RCR approaches bolsters our claim that residual endogeneity may not be a big issue in this study. However, we cannot entirely rule out the possibility of residual endogeneity, necessitating further investigation of this aspect, potentially by using external instruments that satisfy exclusion and relevance assumptions.

https://doi.org/10.1017/age.2023.39

Conclusions

Contract noncompliance has been a challenging issue for the cost-share programs, leading to efficiency loss and increased program expenditures. This paper explores relatively unexplored noncompliance issues in cost-share contracts using historical county-level data of contract allocations and associated payment obligations in two working lands programs, EQIP and CSP, from Louisiana. We observe contract cancellations as a major source of noncompliance, exceeding terminations by approximately threefold. Higher frequency of cancellations is due to flexible provisions within the cancellation category and indicates the presence of hidden incentives. Furthermore, the spatial clusters of noncompliance rates along the Mississippi River and the Red River basin provide compelling evidence of peer effects in the non-completion of conservation contracts. The results also indicate that farmers are more likely to follow contractual terms during periods of increased loss ratio and higher HDD. Conversely, during favorable market conditions, they tend to disregard contractual terms. Such irregularity in implementing conservation practices and the strategic behavior of farmers after signing contracts pose significant challenges to the long-term provisioning of ecosystem services. These findings have important implications for cost-share programs; mitigating the prevailing moral hazard is imperative to encourage the generation of more ecosystem services from private lands.

Our analysis of the effect of the payment obligations shows that a one percent increase in payment rate could reduce the noncompliance rate by ~0.07 percentage points. As both payment obligations and contract acreage are deemed highly consequential in addressing noncompliance, revisiting payment rates and considering acreage during contract allocations could effectively lower inefficient contract withdrawals, mitigate moral hazard, and generate additional ecosystem services. The findings from this study could serve as a valuable reference for funding agencies in future program planning and also provide insights for policymakers as the new Farm Bill is set to roll out soon. Despite some limitations, this study opens avenues for future research by investigating relatively less-explored topics such as the incentive effect and moral hazard concerning US agricultural conservation programs. Future research could incorporate factors such as farmers' risk aversion, contract duration, practice intensity, and practice type (one-time discrete capital projects or multiyear practices) in noncompliance studies. Additionally, researchers could explore the prospects of behavioral or information nudges to overcome noncompliance and better align farmers' motives with the goals of conservation programs.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/age.2023.39.

Data availability statement. Data is available upon request from the corresponding author.

Acknowledgments. The authors greatly appreciate the valuable input received from discussants at the 2022 Sloan/UC Berkeley Summer School in Environmental and Energy Economics, the 2022 Southern Agricultural Economics Association (SAEA) Annual Meeting in New Orleans (LA), and the 2022 Agricultural and Applied Economics Association (AAEA) Annual Meeting in Anaheim (CA). Special thanks to the editor, Trey Malone, and anonymous reviewers for their excellent feedback. The authors also extend their gratitude to Lawson Connor, Wendiam Sawadgo, Archisman Mitra, Raghav Goyal, Mahmut Yasar, Sean Inoue, Catherine Kling, Jerrod Penn, and Hector Zapata for their generous comments and suggestions. All remaining errors are our own.

Funding statement. This study was partly funded by USDA Hatch Project #94538.

Competing interests. None.

References

Adusumilli, N., H. Wang, S. Dodla, and M. Deliberto. 2020. "Estimating Risk Premiums for Adopting No-till and Cover Crops Management Practices in Soybean Production System Using Stochastic Efficiency Approach." *Agricultural Systems*, **178**: 102744. doi: 10.1016/j.agsy.2019.102744

Aillery, M.P. 2006. Contrasting Working-land and Land Retirement Programs. E. R. S. US Department of Agriculture. https://www.ers.usda.gov/webdocs/publications/42910/29511_eb4_002.pdf?v=0

Anselin, L. 1988. Spatial Econometrics: Methods and Models (Vol. 4). Springer Dordrecht. doi: 10.1007/978-94-015-7799-1

Baum, C. F., and A. Lewbel. 2019. "Advice on Using Heteroskedasticity-based Identification." *The Stata Journal*, **19**(4): 757–767. doi: 10.1177/1536867X19893614

Baylis, K., J. Coppess, B.M. Gramig, and P. Sachdeva. 2022. "Agri-environmental Programs in the United States and Canada." *Review of Environmental Economics and Policy*, **16**(1): 83–104. doi: 10.1086/718052

BEA. 2021. *Regional Data*. Bureau of Economic Analysis. https://apps.bea.gov/itable/iTable.cfm?ReqID=70&step=1

Belotti, F., G. Hughes, and A.P. Mortari. 2017. "Spatial Panel-data Models Using Stata." *The Stata Journal*, **17**(1): 139–180. doi: 10.1177/1536867X1701700109

Benítez, P.C., T. Kuosmanen, R. Olschewski, and G.C. van Kooten. 2006. "Conservation Payments Under Risk: A Stochastic Dominance Approach." *American Journal of Agricultural Economics*, **88**(1): 1–15. doi: 10.1111/j.1467-8276.2006.00835.x

Bowles, T.M., M. Mooshammer, Y. Socolar, F. Calderón, M.A. Cavigelli, S.W. Culman, W. Deen, C.F. Drury, A.G. Garcia, and A.C. Gaudin. 2020. "Long-term Evidence Shows that Crop-rotation Diversification Increases Agricultural Resilience to Adverse Growing Conditions in North America." *One Earth*, **2**(3): 284–293. doi: 10.1016/j.oneear.2020.02.007

Cameron, A.C., and P.K. Trivedi. 2005. *Microeconometrics: Methods and Applications*. Cambridge University Press.

Carlsson, F., C. Gravert, O. Johansson-Stenman, and V. Kurz. 2021. "The Use of Green Nudges as an Environmental Policy Instrument." *Review of Environmental Economics and Policy*, **15**(2): 216–237. doi: 10.1086/715524

Cattaneo, A. 2003. "The Pursuit of Efficiency and Its Unintended Consequences: Contract Withdrawals in the Environmental Quality Incentives Program." *Review of Agricultural Economics*, **25**(2): 449–469. doi: 10.1111/1467-9353.00149

Chen, L., R.M. Rejesus, S. Aglasan, S. Hagen, and W. Salas. 2022. "The Impact of No-till on Agricultural Land Values in the United States Midwest." *American Journal of Agricultural Economics* **105**: 760–783. doi: 10.1111/ajae.12338

Claassen, R., A. Cattaneo, and R. Johansson. 2008. "Cost-effective Design of Agri-environmental Payment Programs: US Experience in Theory and Practice." *Ecological Economics* **65**(4): 737–752. doi: 10.1016/j.ecolecon.2007.07.032

Connor, L., R.M. Rejesus, and M. Yasar. 2021. "Crop Insurance Participation and Cover Crop Use: Evidence from Indiana County-level Data." *Applied Economic Perspectives and Policy*, 1–28. doi: 10.1002/aepp.13206

Czap, N.V., H.J. Czap, S. Banerjee, and M.E. Burbach. 2019. "Encouraging Farmers' Participation in the Conservation Stewardship Program: A Field Experiment." *Ecological Economics* **161**: 130–143. doi: 10.1016/j.ecolecon.2019.03.010

Czyżewski, B., and Ł. Kryszak. 2022. Evolution of Agri-environmental Schemes Worldwide. Comparing the Agricultural Policy of the EU, the US and the People's Republic of China. In Sustainable Agriculture Policies for Human Well-Being (pp. 175–193). Springer. doi: 10.1007/978-3-031-09796-6_6#

Dean, A.J., R. Eberhard, U. Baresi, A. Coggan, F. Deane, E. Hamman, K.J. Helmstedt, B. Loechel, D. Jarvis, H. Mayfield, L. Stevens, B. Taylor, and K. Vella. 2023. "Scrutinizing the Impact of Policy Instruments on Adoption of Agricultural Conservation Practices using Bayesian Expert Models." *Conservation Letters*, e12988. doi: 10.1111/conl.12988

Delgado, J.A., P.M. Groffman, M.A. Nearing, T. Goddard, D. Reicosky, R. Lal, N.R. Kitchen, C.W. Rice, D. Towery, and P. Salon. 2011. "Conservation Practices to Mitigate and Adapt to Climate Change." *Journal of Soil and Water Conservation*, **66**(4): 118A–129A. doi: 10.2489/jswc.66.4.118A

Duquette, E., N. Higgins, and J. Horowitz. 2012. "Farmer Discount Rates: Experimental Evidence." *American Journal of Agricultural Economics*, **94**(2): 451–456. doi: 10.1093/ajae/aar067

Featherstone, A.M., and B.K. Goodwin. 1993. "Factors Influencing a Farmer's Decision to Invest in Long-term Conservation Improvements." *Land Economics*, **69**(1): 67–81. doi: 10.2307/3146279

FRS. 2021. *County-Level Debt-to-Income Ratio, 1999-2021*. Board of Governers of the Federal Reserve System. Retrieved 11/18/2021 from https://www.federalreserve.gov/releases/z1/dataviz/household_debt/county/map/#state:all;year:2020

Giannakas, K., and J.D. Kaplan. 2005. "Policy Design and Conservation Compliance on Highly Erodible Lands." *Land Economics*, **81**(1): 20–33. doi: 10.3368/le.81.1.20

Goodwin, B.K. 1993. "An Empirical Analysis of the Demand for Multiple Peril Crop Insurance." *American Journal of Agricultural Economics*, **75**(2): 425–434. doi: 10.2307/1242927

Gow, H.R., D.H. Streeter, and J.F. Swinnen. 2000. "How Private Contract Enforcement Mechanisms can Succeed Where Public Institutions Fail: The Case of Juhocukor A.S." *Agricultural Economics*, **23**(3): 253–265. doi: 10.1111/j.1574-0862.2000.tb00277.x

Gow, H.R., and J.F. Swinnen. 2001. "Private Enforcement Capital and Contract Enforcement in Transition Economies." *American Journal of Agricultural Economics*, **83**(3): 686–690. doi: 10.1111/0002-9092.00191

Gramig, B.M., and N.J. Widmar. 2018. "Farmer Preferences for Agricultural Soil Carbon Sequestration Schemes." *Applied Economic Perspectives and Policy*, **40**(3): 502–521. doi: 10.1093/aepp/ppx041

Grossman, S.J., and O.D. Hart. 1983. "Implicit Contracts Under Asymmetric Information." *The Quarterly Journal of Economics*, **98**: 123–156. doi: 10.2307/1885377

Hart, O. 1995. *Firms, Contracts, and Financial Structure*. Clarendon Press, Oxford.

Holmström, B. 1979. "Moral Hazard and Observability." *The Bell Journal of Economics* **10**(1): 74–91. doi: 10.2307/3003320

Krauth, B. 2016. "Bounding a Linear Causal Effect Using Relative Correlation Restrictions." *Journal of Econometric Methods*, **5**(1): 117–141. doi: 10.1515/jem-2013-0013

Langpap, C., and J. Wu. 2017. "Thresholds, Perverse Incentives, and Preemptive Conservation of Endangered Species." *Journal of the Association of Environmental and Resource Economists*, **4**(S1): S227–S259. doi: 10.1086/692070

LeSage, J., and R. Pace. 2009. *Introduction to Spatial Econometrics* (1st ed., Vol. **1**). Chapman and Hall/CRC. doi: 10.1201/9781420064254

Lewbel, A. 2012. "Using heteroscedasticity to Identify and Estimate Mismeasured and Endogenous Regressor Models." *Journal of Business & Economic Statistics*, **30**(1): 67–80. doi: 10.1080/07350015.2012.643126

Lichtenberg, E. 2019. "Conservation and the Environment in US Farm Legislation." *EuroChoices* **18**(1): 49–55. doi: 10.1111/1746-692X.12214

Liu, P., Y. Wang, and W. Zhang. 2022. "The Influence of the Environmental Quality Incentives Program on Local Water Quality." *American Journal of Agricultural Economics*. doi: 10.1111/ajae.12316

McWherter, B., J. Bauchet, Z. Ma, T. Grillos, N. Asquith, M. Rathjen, and A. Markos. 2022. "Compliance Under Control: Insights from an Incentive-based Conservation Program in Rural Bolivia." *Ecological Economics* **194**: 107317. doi: 10.1016/j.ecolecon.2021.107317

Nouri, A., D.C. Yoder, M. Raji, S. Ceylan, S. Jagadamma, J. Lee, F.R. Walker, X. Yin, J. Fitzpatrick, and B. Trexler. 2021. "Conservation Agriculture Increases the Soil Resilience and Cotton Yield Stability in Climate Extremes of the Southeast US." *Communications Earth & Environment*, **2**(1): 1–12. doi: 10.1038/s43247-021-00223-6

Ozanne, A., T. Hogan, and D. Colman. 2001. "Moral Hazard, Risk Aversion and Compliance Monitoring in Agri-Environmental Policy." *European Review of Agricultural Economics* **28**(3): 329–348. doi: 10.1093/erae/28.3.329

Pannell, D.J., and R. Claassen. 2020. "The Roles of Adoption and Behavior Change in Agricultural Policy." *Applied Economic Perspectives and Policy*, **42**(1): 31–41. doi: 10.1002/aepp.13009

Papke, L.E., and J.M. Wooldridge. 2008. "Panel Data Methods for Fractional Response Variables with an Application to Test Pass Rates." *Journal of Econometrics*, **145**(1-2): 121–133. doi: 10.1016/j.jeconom.2008.05.009

Park, B., R.M. Rejesus, S. Aglasan, S. Hagen, and W. Salas. 2022. "Payments from Agricultural Conservation Programs and Cover Crop Adoption." *Applied Economic Perspectives and Policy*: 1–24. doi: 10.1002/aepp.13248

Pates, N.J., and N.P. Hendricks. 2020. "Additionality from Payments for Environmental Services with Technology Diffusion." *American Journal of Agricultural Economics*, **102**(1): 281–299. doi: 10.1093/ajae/aaz028

Pathak, S., K.P. Paudel, and N.C. Adusumilli. 2021. "Impact of the Federal Conservation Program Participation on Conservation Practice Adoption Intensity in Louisiana, USA." *Environmental Management* **68**(1): 1–16. doi: 10.1007/s00267-021-01477-8

Peterson, J.M., C.M. Smith, J.C. Leatherman, N.P. Hendricks, and J.A. Fox. 2014. "Transaction Costs in Payment for Environmental Service Contracts." *American Journal of Agricultural Economics*, **97**(1): 219–238. doi: 10.1093/ajae/aau071

PRISM Climate Group. 2021. *Oregon State University*. https://prism.oregonstate.edu/

Rabalais, N.N., R.E. Turner, and W.J. Wiseman. 2002. "Gulf of Mexico Hypoxia, Aka "The Dead Zone"." *Annual Review of Ecology and Systematics* **33**(1): 235–263. doi: 10.1146/annurev.ecolsys.33.010802.150513

Ramalho, E.A., J.J. Ramalho, and L.M. Coelho. 2018. "Exponential Regression of Fractional-Response Fixed-Effects Models with an Application to Firm Capital Structure." *Journal of Econometric Methods*, **7**(1): 20150019. doi: 10.1515/jem-2015-0019

Ribaudo, M., and J. Shortle. 2019. "Reflections on 40 Years of Applied Economics Research on Agriculture and Water Quality." *Agricultural and Resource Economics Review*, **48**(3): 519–530. doi: 10.1017/age.2019.32

Del Rossi, G., M.M. Hoque, Y. Ji, and C.L. Kling. 2023. "The Economics of Nutrient Pollution from Agriculture." *Annual Review of Resource Economics*, **15**: 105–130. doi: 10.1146/annurev-resource-111820-021317

Sawadgo, W., and A. Plastina. 2022. "The Invisible Elephant: Disadoption of Conservation Practices in the United States." *Choices*, **37**(1): 1–13. https://www.choicesmagazine.org/UserFiles/file/cmsarticle_822.pdf

Trujillo-Barrera, A., J.M. Pennings, and D. Hofenk. 2016. "Understanding Producers' Motives for Adopting Sustainable Practices: The Role of Expected Rewards, Risk Perception and Risk Tolerance." *European Review of Agricultural Economics* **43**(3): 359–382. doi: 10.1093/erae/jbv038

USDA-ERS. 2023. *U.S. Agricultural Policy Review, 2022*. Economic Information Bulletin Number 260. US Department of Agriculture, Economic Research Service, Washington, D.C., USA.

USDA-FSA. 2021. *CRP Enrollment and Rental Payments by County, 1986-2019*. USDA Farm Service Agency. Retrieved 11/2/2021 from https://www.fsa.usda.gov/Assets/USDA-FSA-Public/usdafiles/Conservation/Excel/HistoryCounty86-19.xlsx

USDA-NASS. 2020. *Quick Stats*. USDA National Agricultural Statistics Service. https://quickstats.nass.usda.gov/

USDA-RMA. 2021. *State/County/Crop Summary of Business*. USDA Risk Management Agency. Retrieved 10/20/2021 from https://www.rma.usda.gov/SummaryOfBusiness/StateCountyCrop

Wallander, S., R. Claassen, A Hill, and J. Fooks. 2019. Working Lands Conservation Contract Modifications: Patterns in Dropped Practices (ERR-262). https://www.ers.usda.gov/webdocs/publications/92644/err-262.pdf?v=9127

Wardropper, C.B., L.A. Esman, S.C. Harden, Y.J. Masuda, P. Ranjan, C. Weigel, P.J. Ferraro, L.S. Prokopy, and S.M. Reddy. 2022. "Applying a "Fail-Fast" Approach to Conservation in US Agriculture." *Conservation Science and Practice* **4**(3): e619. doi: 10.1111/csp2.619

Williams, A., N.R. Jordan, R.G. Smith, M.C. Hunter, M. Kammerer, D.A. Kane, R.T. Koide, and A.S. Davis. 2018. "A Regionally-Adapted Implementation of Conservation Agriculture Delivers Rapid Improvements to Soil Properties Associated with Crop Yield Stability." *Scientific Reports* **8**(1): 1–8. doi: 10.1038/s41598-018-26896-2

Wooldridge, J.M. 2019. "Correlated Random Effects Models with Unbalanced Panels." *Journal of Econometrics*, **211**(1): 137–150. doi: 10.1016/j.jeconom.2018.12.010

Yano, Y., and D. Blandford. 2009. "Use of Compliance Rewards in Agri-environmental Schemes." *Journal of Agricultural Economics* **60**(3): 530–545. doi: 10.1111/j.1477-9552.2009.00208.x

Zabel, A., and K. Holm-Müller. 2008. "Conservation Performance Payments for Carnivore Conservation in Sweden." *Conservation Biology* **22**(2): 247–251. doi: 10.1111/j.1523-1739.2008.00898.x

Cite this article: Pathak, S., H. Wang, and N. C. Adusumilli (2024). "Contract noncompliance in agricultural conservation programs: Panel evidence from Louisiana, USA." *Agricultural and Resource Economics Review* **53**, 251–276. https://doi.org/10.1017/age.2023.39