Comments on “Expanding grass-based agriculture on marginal land in the U.S. Great Plains: The role of management intensive grazing”

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Abstract

A recent paper by Wang et al. (2021) argues that management intensive grazing (MIG) practice adoption might be ' … a key factor for restoring marginal croplands to permanent grassland cover … ' in the United States Northern Great Plains. The matter is important for land use policy because U.S. Federal and State governments actively seek to promote grass cover through a variety of policy instruments. In this note we show that the significant positive coefficient on MIG adoption they estimate in a multivariate ordered probit model does not indicate a valid causal relationship. Their estimates are vulnerable to bias and inconsistency due to potential endogeneity and so do not support their policy inference.

Keywords: Endogeneity, land use conversion, management intensive grazing, instruments

Comments on "Expanding grass-based agriculture on marginal land in the U.S. Great Plains: The role of management intensive grazing"

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1. Introduction

A recent paper by Wang et al. (2021) raises novel policy issues for land use. Through a multivariate ordered probit model estimated on U.S. Great Plains land use, they establish a negative correlation between grazing intensity and land-use conversion from grass agriculture to annual crop production. As a consequence, they argue that management intensive grazing (MIG) practice adoption might be ' … a key factor for restoring marginal croplands to permanent grassland cover … '. The adoption choice is, however, also producer's decision and there is reason to suspect that any correlation between the two decisions might not represent a causal relationship. Their estimates are vulnerable to bias and inconsistency due to potential endogeneity.

The main possible source of the endogeneity in this case is from omitted variables that affect both land-use decisions and grazing practice choices. Omitted variables include beef prices and also some unobservable rancher characteristics such as personal preferences and family traditions, which are not documented in the dataset. For example, price shocks in the beef market could induce endogeneity by influencing both decisions. That is, if we run a regression with land-use conversion choice as the dependent variable and MIG adoption as an explanatory variable in the manner of Wang et al. (2021) then we may observe a significant positive coefficient on MIG adoption but only because both MIG adoption and grass cover increase with beef price. As we argue below, the coefficient arrived at does not indicate a valid causal

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relationship.

2. Endogeneity

2.1 Econometric issues

In econometrics, the endogeneity issue describes any situation where an explanatory variable in an econometric equation is correlated with the disturbance. The main source of endogeneity in this case may well be omitted variable(s)[1]. Figure 1, adapted from Pearl (2009), describes alternative possible relationships between land-use conversion, as the dependent variable, and grazing practice adoption, as a variable that may help to explain land-use conversion. We worry that grazing practice decisions, including RG and MIG adoption, cannot be viewed as driving factors as depicted in the figure's Panel A. Because they are likely correlated with some omitted driving factors, possibly related to price shocks in the beef market or unobservable rancher characteristics, which also affect land-use decisions, additional care must be taken when seeking to understand the roles they play in land cover choice decisions. In addition, simultaneity and measurement error may also exist. For example, the grazing practice choice could also be partly determined by the land-use conversion decision. Measurement error in the adoption of RG or MIG is also a possibility, in part because these variables may be interpreted differently. The three possible forms of endogeneity are often hard to distinguish between (Wooldridge, 2010), and to make our point we focus on omitted variables in this research. Application of instruments is one approach to addressing endogeneity. We will discuss this approach after laying out the conceptual issues that underscore our comment.

2.2. Conceptual issues

[1] Endogeneity usually arises from some combination of three sources: (i) omitted variable(s) in which one or more additional variables should be included as explanatory variables in a regression model but were not included due to mis-specification or data unavailability; (ii) simultaneity in which one or more variables held to be explanatory are determined simultaneously along with the dependent variable; (iii) measurement error in which perfect measurement of an independent variable is impossible (Greene, 2000; Wooldridge, 2010).

We develop a simple framework to explain the estimation bias that we are concerned about. To do so we model three factor categories affecting grass-based production. These are factors that

i) (directly only) influence the land conversion choice but do not influence grazing practice adoption. These are labeled as γ.

ii) (indirectly only) influence the grazing practice adoption decision and through it indirectly influence grass-based production. These are labeled as β and, for reasons to be explained shortly, are also referred to as instruments.

iii) (both ways) may affect grass-based production both directly and also indirectly through the grazing practice adoption channel. Labeled as α, any omitted variables causing endogeneity belong to this category.

Assignment of factors to these categories is a matter of judgement regarding degree because arguments can typically be made that any factor has at least some direct and at least some indirect influence. An example of a factor adhering to the first is the beef cattle farm gate price where one would expect that a price increase will likely increase both the incentive to graze and the incentive to graze more intensively on any grazing land. An example of the second is a subsidy on intensive grazing or on an input that is in greater need under intensive grazing. A subsidy on fencing or water provision are examples, as is extension advice designed in support of intensive grazing. Examples of the third are the prices of crops or inputs used primarily in crop production, e.g., pesticides or corn seeds, or technologies that reduce the cost of producing non-grass crops, including herbicide-tolerant seeds or no-till technologies. Crop insurance programs that favor non-grass cover are other examples.

Considering the above three factor categories, we model the extent of grass-based production as function relation $G(\alpha,\beta,\gamma) = f[M(\alpha,\beta),\alpha,\gamma]$, where $M(\alpha,\beta)$ represents the adoption of MIG. Therefore, corresponding to Panel B in Figure 1, we may write:

(1i) Directly only: $\dfrac{dG(\cdot)}{d\gamma} = \dfrac{\partial f(\cdot)}{\partial \gamma}$;

(1ii) Indirectly only: $\dfrac{dG(\cdot)}{d\beta} = \dfrac{\partial f(\cdot)}{\partial M}\dfrac{dM(\cdot)}{d\beta}$; (1)

(1iii) Both ways: $\dfrac{dG(\cdot)}{d\alpha} = \overbrace{\dfrac{\partial f(\cdot)}{\partial \alpha}}^{\text{Direct effect}} + \overbrace{\dfrac{\partial f(\cdot)}{\partial M}\dfrac{dM(\cdot)}{d\alpha}}^{\text{Indirect effect}}$.

An alternative way of considering responses is to ignore the arguments that influence $M(\cdot)$ and write instead an abbreviated expression for the determination of grassland production level, $\widehat{G} = f[M, \alpha, \gamma]$. Then, and corresponding to Panel A in Figure 1, responses are:

(2i) $\dfrac{d\widehat{G}(\cdot)}{d\gamma} = \dfrac{\partial f(\cdot)}{\partial \gamma}$.

(2ii) $\dfrac{d\widehat{G}(\cdot)}{dM} = \dfrac{\partial f(\cdot)}{\partial M}$; (2)

(2iii) $\dfrac{d\widehat{G}(\cdot)}{d\alpha} = \overbrace{\dfrac{\partial f(\cdot)}{\partial \alpha}}^{\text{Direct effect}}$;

The first derivative in each case, for directly only, matches across (1) and (2) but the other two derivatives do not. In Figure 1, Panel B, and consistent with System 1, α are factors on both arrows leaving the 'Driving factors' box, γ are factors only on the direct arrow to 'Land use conversion decision' and β are factors only on the arrow from 'Instruments' to 'Grazing practice decision.' Panel A, for System 2, corresponds to the framework provided in Wang et al. (2021). Regarding policy prescription, the mismatch between the two systems is revealing. The policy approach for influencing land cover via grazing technology adoption will not be to dictate grazing practices, which are largely beyond the direct control of policy makers, but rather to influence practice choices through factors in the set β.

There is also an econometric concern with system (2). Factors in set α will induce a correlation between *M* and *G* even when there is no causal relationship. For example, an increase in beef prices will likely increase both grazing intensity and grassland cover. The consequent positive correlation may be reflected in a positive coefficient on M in any estimation of specification $\widehat{G} = f[M, \alpha, \gamma]$ that does not acknowledge the endogenous nature of M. However, this response may be biased as some of the direct route effects of change in α on land use may be ascribed to the indirect route and so ascribed to M because changes in α cause changes in M as well as in G. The root cause of this problem is that the grazing practice adoption variable is a choice variable, i.e., it is endogenous.

2.3. Instrumental variables

To address this endogeneity, we employ the instrumental variables (IVs) approach in the multivariate ordered probit model. The IV method provides a general solution to endogeneity (Wooldridge, 2010). Thus, we estimate the multivariate ordered probit model with IVs on three land-use conversion decisions[2] by a seemingly unrelated regressions (SUR) framework employing the conditional mixed-process (CMP) technique developed by Roodman (2011). Our modeling approach seeks to address the endogeneity issue through the application of IVs, but is otherwise as in Wang et al. (2021).[3] This similarity allows us to demonstrate the extent of bias that can result from endogenous grazing practice decisions by comparing the estimates obtained in their study with those obtained in this study.

Generally, an IV is a variable that is correlated with the endogenous independent variable but uncorrelated with the regression's error term. However, the approach is often hindered by a lack of suitable instruments in a dataset. Nonetheless we endeavor to choose four instruments for RG and MIG adoption. The four are:

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[2] These are: Y_1 = grassland acres change during the past 10 years; Y_2 = purchasing or leasing more grassland over the subsequent 10 years; Y_3 = cropland to grassland conversion over the subsequent 10 years. Detailed descriptions of the three categorical dependent variables can be found in Wang et al. (2021).

[3] Although we present the analysis for Y_1, we are of the view that the causal direction is invalid: when Wang et al. (2021) examine how current RG/MIG adoption affects grass acres change over the preceding 10 years, any causal relationship should run in the other direction.

1. "Internal fencing": Respondents were asked whether they had some internal or cross fencing on the ranch before adopting RG or MIG.

2. "Ranch conditions": Respondents were asked to rate the ranch condition challenges (such as size and water availability issues) that they had encountered when practicing RG or MIG, or how the challenge in question hinders their adoption decisions. Five options were given: 1 = 'not a challenge', 2 = 'minor challenge', 3 = 'some challenge', 4 = 'quite a challenge', and 5 = 'great challenge.'

3. "RG profit"[4]: Respondents were asked how the adoption of RG had affected or would likely affect ranch economic profit during the first five years when compared to continuous grazing (CG). Five available options were: 1 = 'significantly decreased', 2 = 'slightly decreased', 3 = 'no influence', 4= 'slightly increased', and 5 = 'significantly increased.'

4. "RG labor": Respondents were asked how the adoption of RG had affected or would likely affect the amount of required labor and management time when compared to CG, with response alternatives as given under "RG profit" above.

Valid instruments must be *i*) correlated with the endogenous variable (grazing practice adoption choices), and *ii*) uncorrelated with the error term. We argue that the selected variables satisfy both criteria and as such are legitimate instruments under some circumstances. The lines and arrows in the path diagram in Figure 1 also outline the above two requirements. Detailed supporting arguments are stated as follows.

- Regarding condition *i*), the selected variables are correlated with producers' grazing practice adoption choices. To be specific, implementation of RG or MIG needs additional fencing costs (Windh et al., 2019), so the existence of internal fencing is more helpful for RG

[4] The "MIG profit" variable is not included since it is highly correlated with "RG profit", where the Pearson correlation coefficient is 0.781. Nor do we include "MIG labor", which is correlated with "RG labor", Pearson correlation = 0.693. In addition, many "MIG profit" and "MIG labor" observations are missing. For each, about 56% of respondents did not report any information.

or MIG than for CG. Ranch condition, and especially lack of water resources, is a particularly acute challenge for RG or MIG adoption when compared with CG because water must be made available in multiple locations. Also, RG or MIG usually requires more labor (Gillespie et al. 2008) when compared with CG, so the difference in labor requirements between more intensive grazing and CG will affect producers' technology choices. Similarly, the perceived profit change in RG compared to CG will also influence producers' adoption decisions.

- Condition *ii*) requires that the instruments be uncorrelated with the land-use decision equation error term. Given the current CG status, the existence of internal fencing is a beneficial factor for RG/MIG adoption, while adverse ranch conditions are a challenge. So these two variables will affect whether to switch from CG to RG/MIG. Apart from the inconvenience of dealing with fencing during cropping operations, this infrastructure is not correlated with the grass vs. crop land-use decision. Also the "RG labor" and "RG profit" variables both measure commensurable differences between RG and CG. They should only affect the choice between these two grazing practices and not the land conversion decision.

3. Empirical analysis

We use the same survey data and variables as Wang et al. (2021). Estimation results for the multivariate ordered probit models with IVs are presented in Table 1. After controlling for other potential factors that can affect ranchers' land-use decisions, we find no significant differences in the land-use decisions between CG and either RG or MIG adopters. This point contrasts with Wang et al. (2021), who find that MIG adoption is associated with significantly greater increases in grassland acres in the past and with potential future cropland to grassland conversion. In addition, the estimated results for other potential factors are very similar to corresponding values in Wang et al. (2021).

As a robustness check, we combine RG adoption and MIG adoption into a single variable, i.e., the RG/MIG adoption variable equals 1 whenever a rancher was either an RG adopter or a

MIG adopter, and equals 0 otherwise. The estimated effect of the unified RG/MIG choice on land-use decisions remains insignificant (Table 2). This finding supports the statement that the direct effect of MIG adoption on land-use conversion is not significant upon accounting for endogeneity. Details on IV estimation and results as well as further robustness checks are provided in the Supplemental Material.

4. Conclusion

Endogeneity arises when seeking to ascertain causal relationships in many social science research fields and can have significant consequences for policy assessment (Pearl, 2009). Because the endogeneity issue can lead to biased and inconsistent estimates and because there are strong *prima facie* grounds to suspect its presence in the matter at hand, we conclude that the Wang et al. (2021) study does not support their policy inference. While the instrumental variable approach is effective in accounting for endogeneity, the extent of effectiveness depends on having informative data on suitable instrument variables. We note that our estimates are restricted by the limited instrumental variables that we could find. However, having sought as best we could to address endogeneity we do not find evidence that rotational grazing or management intensive grazing affect land-use conversion decisions. To be clear, we are not suggesting that policies to promote RG or MIG will fail to increase grassland cover. That such policies will succeed in doing so is, in our view, a reasonable hypothesis as is the more demanding hypothesis that the benefits of such policies exceed the costs. We only conclude that the survey data at issue and the methods used both in Wang et al. (2021) and this comment do not identify a significant response. The correlation between MIG adoption and land-use conversion may be due to some omitted confounders, including beef prices or unobservable rancher characteristics, that cross-sectional survey data collection approaches are not well-suited to address. One final comment is that, quite aside from empirical considerations, the conceptual approach in Figure 1, Panel A, is of limited use when prescribing policy. It does not show how grazing practice decisions are to be modified. The instruments in Panel B can be both econometric and policy in nature. For example, subsidies on internal fencing can be costed and their impacts estimated to establish the costs and benefits of changing land use choice through grazing practice decisions.

Acknowledgements

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Figures and Tables

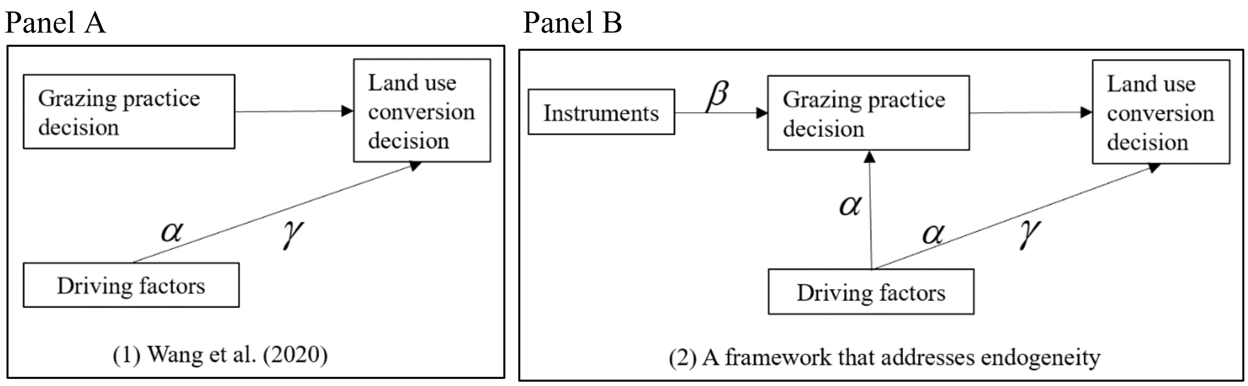

Figure 1 Path diagrams for endogeneity and instruments

Table 1
Estimated coefficients and standard errors (SE) for the multivariate ordered probit - IV model.

	Grassland acres change (Y_1)		Purchasing/leasing more grassland (Y_2)		Cropland to grassland conversion (Y_3)	
Variable	Coefficient	SE	Coefficient	SE	Coefficient	SE
RG adoption	-0.225	0.186	-0.183	0.178	0.222	0.180
MIG adoption	0.471	0.351	-0.162	0.349	-0.090	0.373
Environmental priority	0.046	0.062	0.008	0.059	0.141^{b}	0.057
Age	-0.021^{a}	0.005	-0.034^{a}	0.005	-0.011^{b}	0.004
Extension & gov. agency	0.056	0.044	0.103^{b}	0.042	0.097^{b}	0.040
Gross sales	0.259^{a}	0.039	0.210^{a}	0.038	0.043	0.035
Liability ratio	0.050	0.036	0.082^{b}	0.034	0.052	0.033
Slope less than 3%	0.099	0.149	0.327^{b}	0.140	-0.098	0.132
LCC I to IV	0.048	0.160	-0.260^{c}	0.152	-0.108	0.144
Precipitation (10^3 mm)	-0.123	0.347	-0.493	0.336	-0.538^{c}	0.314
Texas	0.200	0.157	0.489^{a}	0.152	0.136	0.142
Intercept 1	0.144	0.443	-2.170^{a}	0.434	-0.933^{b}	0.409
Intercept 2	0.634	0.445	-1.193^{a}	0.431	0.145	0.407
ρ_{12}	0.331^{a}	0.060				
ρ_{13}	0.193^{a}	0.058				
ρ_{23}	0.284^{a}	0.052				
Observations	732		$\chi^2(59)$ =373.89			
Log-likelihood	-2,299.1		Prob > chi-squared = 0.000			

Note: ^{a} *p<0.01,* ^{b} *p<0.05,* ^{c} *p<0.1.* "Internal fencing", "ranch condition", "RG labor", and "RG profit" are IVs for RG adoption and MIG adoption. The observation number of 732 is less than 748 in Wang et al. (2021), because they set the environment priority variable as 0 when there were missing data in either environmental goals or profit goals. We correct by coding these zero values as missing.

Table 2
Estimated coefficients and standard errors (SE) for the multivariate ordered probit – IV model including combined RG/MIG adoption as an explanatory variable

	Grassland acres change (Y_1)		Purchasing/leasing more grassland (Y_2)		Cropland to grassland conversion (Y_3)	
Variable	Coefficient	SE	Coefficient	SE	Coefficient	SE
RG/MIG adoption	-0.129	0.183	-0.184	0.172	0.182	0.174
Environmental priority	0.071	0.061	0.009	0.058	0.132^{b}	0.056
Age	-0.022^{a}	0.005	-0.034^{a}	0.005	-0.011^{b}	0.004
Extension & gov. agency	0.062	0.044	0.103^{b}	0.042	0.095^{b}	0.040
Gross sales	0.259^{a}	0.039	0.210^{a}	0.038	0.043	0.035
Liability ratio	0.049	0.036	0.083^{b}	0.034	0.053	0.033
Slope less than 3%	0.101	0.149	0.327^{b}	0.140	-0.099	0.132
LCC I to IV	0.047	0.161	-0.261^{c}	0.152	-0.107	0.145
Precipitation (10^3 mm)	-0.095	0.347	-0.491	0.335	-0.559^{c}	0.313
Texas	0.192	0.157	0.488^{a}	0.152	0.142	0.142
Intercept 1	0.176	0.444	-2.171^{a}	0.433	-0.955^{b}	0.408
Intercept 2	0.667	0.445	-1.194^{a}	0.430	0.130	0.407
ρ_{12}	0.339^{a}	0.058				
ρ_{13}	0.215^{a}	0.055				
ρ_{23}	0.286^{a}	0.051				
Observations	732		$\chi^2(43)$ =355.55			
Log-likelihood	-2,342.9		Prob > chi-squared = 0.000			

Note: ^{a} *p<0.01,* ^{b} *p<0.05,* ^{c} *p<0.1.* "Internal fencing", "ranch condition", "RG labor" and "RG profit" are IVs for RG/MIG adoption

Supplemental Materials

SM1. Empirical analysis with two additional explanatory variables

In the main text, we seek to maintain the same set of explanatory variables as in Wang et al. (2021) so that results are comparable between the two studies. However, we conjecture that two additional variables will potentially affect land-use conversion decisions in the regression. One additional variable is "cropland share", which represents cropland acres as a share of total farm acres; the other is "hay area share", which denotes area planted to hay/forage as a share of total farm acres. Summary statistics for these two variables and comparisons between Dakotas and Texas producers can be found in Table S1. Producers in the Dakotas planted larger shares of their land to cropland and to hay or forage than did their peers in Texas. We suppose the producers' land-use decisions might be affected by the current land status, including the cropland and planted area for hay or forage. In addition, we correct the statistics for the "environmental priority" variable which were in error due to missing observations that were miscategorized.[i] Table S1 also reports the summary statistics, a comparison of "environmental priority", and also some other corrected variables[ii] for Dakotas and Texas producers.

We examine the effects of current land status on producers' land-use conversion decisions by including "cropland share" and "hay area share", since we conjecture that land-use conversion can potentially be affected by the proportion of cropland and also the planted area for hay and forage that might be readily converted into grassland. The estimated coefficients can be found in

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[i] We find an issue related to missing data when constructing the "environmental priority" variable. Wang et al. (2021) set the environment priority variable as 0 when there were missing data in either environmental goals or profit goals. We correct by coding these zero values as missing. As a consequence the overall average value of the environment priority variable is updated to 0.808 with 842 observations, see Table S1. This change does not affect the finding that respondents on average viewed environmental goals as being less important than profit goals.

[ii] There were typos in the mean values of RG adoption and MIG adoption and the number of liability ratio observations in Texas in Wang et al. (2021), and we make corrections in Table S1.

Table S2. We find that ranchers with more acres planted to hay as a share of total acres were more likely to increase grassland in the past and convert grassland to cropland in the future. This is because land planted to hay or forage is easier to convert to grassland than are other types of croplands. However, there is no evidence that the adoption of MIG will promote the conversion from cropland to grassland.

Similar to the robustness check in the main text, we combine RG and MIG adoption into a single variable, i.e., the RG/MIG adoption variable equals 1 whenever a rancher was an RG adopter or a MIG adopter, otherwise, it equals 0. We examine the effects of general rotational grazing adoption on land use decisions. We apply similar multivariate ordered probit models with four instrumental variables including two additional explanatory variables "cropland share" and "hay area share". Estimated coefficients can be found in Table S3. Here too we find no significant effects of rotational grazing adoption on land use decisions.

SM2. Tests for instruments

In this section we would like to conduct endogeneity tests and weak instrument tests. Since it is hard to do the above tests in the multivariate ordered logit model with instruments by the CMP, we estimate a linear probability model by using generalized method of moments (GMM) estimators and we complete the tests. To adapt the linear probability model, we transform the three categorical variables ($Y_1,\ Y_2,\ Y_3$)[iii] into binary variables (Y_1', Y_2', and Y_3').[iv] The framework can be written as:

$$Y_i' = \beta_{0i} + \beta_{1i}A + \beta_{2i}X + \varepsilon_i,\ i = 1,2,3 \tag{S1}$$

[iii] Detailed descriptions of Y_1, Y_2, and Y_3 can be found in Wang et al. (2021).

[iv] For Y_1', 0 = 'no increase,' including 'decreased by >10%', 'decreased by 5-10%' and 'about the same,' while 1 = 'increased by 5%-10%', and 'increased by >10%'. For Y_2' and Y_3', 0 = 'very unlikely,' and 'unlikely,' while 1 = 'somewhat likely,' 'likely,' and 'very likely.'

$$A = \alpha_0 + \alpha_1 X + \alpha_2 Z + \nu \qquad \text{(S2)}$$

where A denotes grazing practice adoption variables (RG adoption, MIG adoption, or RG/MIG adoption), all the other explanatory variables are denoted as X, the instruments for grazing practice adoption variables are denoted as Z, and the error terms are ε_i and ν.

The regression results are presented in Table S4, in which we also report some tests for instruments and identifications. First, the underidentification test[v] is used to test for the first condition of instruments, namely that the instruments are correlated with the endogenous regressor. The test results show that the first condition holds when the combined RG and MIG adoption variable is included. Second, the overidentification test[vi] is used to test for the second condition of instruments, namely that instruments are uncorrelated with the error term. The results indicate that the second condition holds for most estimations, but not for the cases with future grassland expansion as the dependent variable. Third, for the test of endogeneity[vii], *p*-values for the C statistics (Hayashi 2000) indicate that we cannot reject the null hypothesis that RG adoption, MIG adoption or RG/MIG adoption are exogenous. Finally, we follow the weak instrument tests by Stock and Yogo (2005). The first-stage F-statistics show that our instruments are weak for RG adoption and MIG adoption, but are strong for the combined RG/MIG adoption variable.

[v] The underidentification test null hypothesis is that the instruments are not correlated with the endogenous regressor.
[vi] The overidentification test null hypothesis is that the instruments are uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation.
[vii] The endogeneity test null hypothesis is that the specified endogenous regressors can actually be treated as exogenous.

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Table S1
Summary statistics and comparison of explanatory variables, North Dakota, South Dakota and Texas producers combined.

	All Sample					Dakotas			Texas		
Variable	Obs.	Mean	Std Dev.	Min	Max	Obs.	Mean	Std Dev.	Obs.	Mean	Std Dev.
RG adoption[a]	874	0.527	0.5	0	1	549	0.574	0.495	325	0.449	0.498
MIG adoption	874	0.068	0.251	0	1	549	0.075	0.263	325	0.055	0.229
Environmental priority	842	0.808	0.787	0	2	532	0.788	0.78	310	0.842	0.799
Liability ratio[a]	791	2.622	1.299	1	6	500	2.764	1.291	291	2.378	1.279
Cropland share[a]	825	0.216	0.259	0	1	514	0.292	0.271	311	0.09	0.178
Hay area share[a]	825	0.087	0.115	0	0.948	514	0.101	0.103	311	0.062	0.128

Note: [a] indicates that variable means between Dakotas and Texas are different at the 0.01 significance level, based on both pooled and Satterthwaite t-tests. This table only presents variables for which i) we either corrected typos, or ii) were not included in Wang et al. (2021). The other explanatory variables can be found in Wang et al. (2021).

Table S2
Estimated coefficients and standard errors (SE) for multivariate ordered probit estimations with “internal fencing”, “ranch condition”, “RG labor”, and “RG profit” as IVs by CMP (including cropland share and hay area share)

	Grassland acres change (Y_1)		Purchasing/leasing more grassland (Y_2)		Cropland to grassland conversion (Y_3)	
Variable	Coefficient	SE	Coefficient	SE	Coefficient	SE
RG adoption	-0.188	0.192	-0.174	0.183	0.308[c]	0.183
MIG adoption	0.509	0.356	-0.112	0.351	-0.018	0.372
Environmental priority	0.036	0.063	-0.022	0.059	0.133[b]	0.058
Age	-0.023[a]	0.005	-0.033[a]	0.005	-0.009[b]	0.004
Extension & gov. agency	0.067	0.046	0.110[b]	0.043	0.100[b]	0.041
Gross sales	0.263[a]	0.040	0.210[a]	0.039	0.046	0.036
Liability ratio	0.057	0.037	0.078[b]	0.035	0.053	0.033
Slope less than 3%	0.144	0.152	0.337[b]	0.141	-0.103	0.134
LCC I to IV	0.049	0.169	-0.272[c]	0.160	-0.167	0.152
Precipitation (10^3 mm)	-0.131	0.353	-0.472	0.340	-0.500	0.318
Texas	0.218	0.170	0.495[a]	0.161	0.166	0.150
Cropland share	-0.283	0.222	-0.115	0.199	0.105	0.193
Hay area share	1.120[b]	0.449	0.486	0.420	0.783[b]	0.389
Intercept 1	0.179	0.461	-2.116[a]	0.451	-0.682	0.425
Intercept 2	0.678	0.463	-1.126[b]	0.448	0.404	0.423
ρ_{12}	0.306[a]	0.060				
ρ_{13}	0.168[a]	0.059				
ρ_{23}	0.274[a]	0.053				
Observations	707		$\chi^2(69) = 386.42$			
Log-likelihood	-2219.1		Prob > chi-squared = 0.000			

Note: [a] $p<0.01$, [b] $p<0.05$, [c] $p<0.1$

Table S3
Estimated coefficients and standard errors (SE) for multivariate ordered probit estimations with "internal fencing", "ranch condition", "RG labor" and "RG profit" as IVs for RG/MIG adoption (including cropland share and hay area share)

	Grassland acres change (Y_1)		Purchasing/leasing more grassland (Y_2)		Cropland to grassland conversion (Y_3)	
Variable	Coefficient	SE	Coefficient	SE	Coefficient	SE
RG/MIG adoption	-0.095	0.190	-0.170	0.177	0.265	0.177
Environmental priority	0.058	0.063	-0.020	0.059	0.125^b	0.057
Age	-0.023^a	0.005	-0.033^a	0.005	-0.009^b	0.004
Extension & gov. agency	0.073	0.046	0.111^a	0.043	0.099^b	0.041
Gross sales	0.263^a	0.040	0.210^a	0.039	0.047	0.036
Liability ratio	0.057	0.037	0.078^b	0.035	0.054	0.033
Slope less than 3%	0.151	0.152	0.338^b	0.141	-0.106	0.134
LCC I to IV	0.054	0.170	-0.271^c	0.160	-0.166	0.152
Precipitation (10^3 mm)	-0.105	0.354	-0.468	0.339	-0.519	0.317
Texas	0.195	0.170	0.492^a	0.161	0.178	0.150
Cropland share	-0.344	0.221	-0.119	0.198	0.125	0.192
Hay area share	1.073^b	0.449	0.483	0.420	0.797^b	0.390
Intercept 1	0.201	0.462	-2.114^a	0.450	-0.704^c	0.425
Intercept 2	0.702	0.464	-1.125^b	0.447	0.388	0.424
ρ_{12}	0.311^a	0.059				
ρ_{13}	0.191^a	0.056				
ρ_{23}	0.277^a	0.052				
Observations	707		$\chi^2(51) = 367.61$			
Log-likelihood	-2260.6		Prob > chi-squared = 0.000			

Note: ^{a} *p<0.01,* ^{b} *p<0.05,* ^{c} *p<0.1*

Table S4

Results for linear probability regression by two-stage least squares

Variable	(1) Y_1'		(2) Y_2'		(3) Y_3'		(4) Y_1'	(5) Y_2'	(6) Y_3'
RG adoption	0.096		0.037		0.146				
MIG adoption	-0.858		-1.399		0.086				
RG/MIG adoption							-0.004	-0.102	0.139
Environmental priority	0.047		0.032		0.061		0.018	-0.011	0.059[b]
Age	-0.011[a]		-0.014[a]		-0.003		-0.009[a]	-0.012[a]	-0.003[c]
Extension & gov. agency	0.015		0.038		0.038[b]		0.013	0.034[c]	0.038[b]
Gross sales	0.072[a]		0.092[a]		0.001		0.069[a]	0.087[a]	0.001
Liability ratio	0.007		0.022		0.019		0.007	0.019	0.019
Slope less than 3%	0.034		0.136[c]		-0.048		0.021	0.131[b]	-0.048
LCC I to IV	0.042		-0.010		0.018		0.028	-0.039	0.017
Precipitation (103 mm)	0.016		-0.182		-0.218		-0.015	-0.231[c]	-0.221[c]
Texas	0.061		0.214[a]		0.091		0.073	0.225[a]	0.091
	Practice adopted								
First stage instruments coefficients	RG	MIG	RG	MIG	RG	MIG	RG/MIG	RG/MIG	RG/MIG
IV1: internal fencing	0.012	0.032	0.010	0.033[c]	0.009	0.033[c]	0.044	0.043	0.042
IV2: ranch conditions	-0.026[c]	-0.016[c]	-0.026[c]	-0.015[c]	-0.027[c]	-0.016[c]	-0.041[a]	-0.042[a]	-0.043[a]
IV3: RG labor	-0.169[a]	-0.002	-0.170[a]	-0.004	-0.168[a]	-0.004	-0.171[a]	-0.174[a]	-0.172[a]
IV4: RG profit	0.066[b]	0.012	0.064[b]	0.013	0.062[b]	0.014	0.079[a]	0.077[a]	0.076[a]
Underidentification test (Kleibergen-Paap rk LM statistic) (P-value)	0.348		0.358		0.353		0.000	0.000	0.000
Overidentification test (Hansen J statistic) (P-value)	0.178		0.740		0.026		0.161	0.295	0.063
Weak identification test (Kleibergen-Paap rk Wald F statistic)	0.828		0.809		0.818		27.850	27.512	24.829

Endogeneity test (P-value)	0.436	0.110	0.953	0.460	0.228	0.769
Observations	602	599	594	602	599	594

Note: [a] p<0.01, [b] p<0.05, [c] p<0.1