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Farmers and Habits: The Challenge of Identifying the Sources of Persistence in Tillage Decisions

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Research Questions

- Do temporary program payments results in persistent practice adoption?
- Why does persistence matter? A simulation exercise for soil carbon benefits.
- Is persistence a general property of no-till adoption? Analysis of Survey Data
- Do we observe post-program persistence in residue levels? Analysis of Satellite and Conservation Program Data.



The No-Till Farming Practice

- Conventional tillage eliminates prior crop residue before planting.
- No-till farming involves planting without tillage and leaves crop residue in place (see photo).



Program Participation and No-Till

Overall adoption of No-Till

1990: 20 million acres (Source: CTIC cited in Hill)

1994: 39 million acres (Source: CTIC)

2012: 96 million acres (Source: USDA Census of Ag.)

1996 to 2016: About 4 million acres enrolled in no-till through USDA EQIP. (Exact acreage is difficult to establish in early years.)

Other factors driving the expansion:

- Seed technology (herbicide resistance)
- Planter technology (seeders and drillers)
- Conservation compliance rules for highly erodible land



Literature

- Persistence in consumer preferences (Keane, 2013)
- Long-term tillage sequences (Wade and Claassen, 2017)
- Crop choice and Markov models (Hua et al, 2005; Ji et al., 2015; Wang et al. 2015)
- Soil carbon and permanent adoption of no till (Antle et al, 2007; Feng et al. 2006)



A Simulation of Soil Carbon Sequestration Costs

- Long-run no-till can remove carbon (CO₂) from the atmosphere and sequester it in the soil.
- Soil carbon sequestration faces two challenges:
 - Additionality: The proportion of sequestered carbon that would not have occurred otherwise.
 - Permanence: The carbon must stay in the soil and not be released by future tillage operations.
- How much persistence is needed for no-till payments to be cost-effective sequestration?



Estimating the Cost of Effective Carbon Sequestration

- We examine how persistence and other factors change the average cost of carbon sequestration in a stylized conservation program.
- Key assumptions:
 - Contracts: Annual payments for 3 years of no-till
 - Saturation: Total sequestration over twenty years
 - Baseline: Transition from conventional tillage
 - Additionality: Based on literature for no-till
 - Impermanence: No sequestration for non-persistence



Variation in the Cost per Ton of CO2

Conventional to No-Till Conversion Scenario

CO2 sequestered	Annual Payment Per Acre		
25.67	Annual Payment Per Acre		
47%	Annual Payment Per Acre		
Permanence	\$15	\$23	\$40
10%	\$37.30	\$57.19	\$99.46
50%	\$7.46	\$11.44	\$19.89
80%	\$4.66	\$7.15	\$12.43

Total CO2 sequestered in tons per acres. Costs in dollars per ton of carbon dioxide equivalent. Bold values are below the \$42 estimated net present value of damages of damages per ton of CO2 emission in 2020 at a 3% discount rate (EPA (2016) social cost of carbon.)



Survey Background

- The USDA ARMS Phase 2 survey provides data on long-term no-till adoption.
 - Nationally representative, field-level
 - Targeted crop varies by survey year
 - Captures up to five years of crop history and no-till history for each field
- These data can be used to look at tillage persistence in general. Detailed data on prior conservation program participation are not available for Phase 2.



Share of Fields with No-Till

	2010 Corn	2011 Barley	2011 Sorghum	2012 Soybeans	2013 Rice	2013 Peanuts
2013					6.91%	8.03%
2012				40.31%	23.20%	34.49%
2011		27.55%	49.20%	41.18%	18.49%	29.96%
2010	24.48%	39.29%	42.80%	45.23%	20.30%	26.76%
2009	34.27%	38.83%	52.21%	41.52%	18.85%	36.66%
2008	30.79%	37.82%	49.82%	47.10%		
2007	31.29%	41.46%	69.84%			
2006	31.48%					

Note: These percentages are shares (using survey weights) of fields that report being in no-till according to the crop history table and (for the survey year) according to the farm operations table and other questions. All fields are growing the indicated crop in the survey year. In the earlier years fields frequently grow other crops.



Markov Order

- A fundamental methodological question is the extent to which prior tillage decisions influence current tillage decisions: the order of the Markov process.
- In examining the sequences of no-till adoption, we find evidence that tillage can be modeled as a second order Markov process.



Likelihood of No-Till Following a Year when the Field was Tilled

Survey	Prior Two Year Tillage Sequence		Impact of No-Till Two Years Back
	Till -> Till	No-Till -> Till	
	Probability of No-Till		
2010 Corn	5.66%	51.55%	45.89%
2012 Soybeans	6.85%	60.64%	53.79%
2011 Sorghum	9.90%	30.20%	20.30%
2011 Barley	7.01%	35.34%	28.33%
2013 Rice	3.94%	55.03%	51.09%
2013 Peanuts	4.64%	37.28%	32.64%

Note: These percentages are shares of fields (using survey weights) according to the farm operations table and other questions. Since fields are observed for (up to) five years, and two years are used for the information on lagged tillage decisions, there are (up to) three years of transitions observed for each field.



Likelihood of No-Till Following a Year when the Field was in No-Till

Prior Two Year Tillage Sequence

Till -> No-Till No-Till -> No-Till

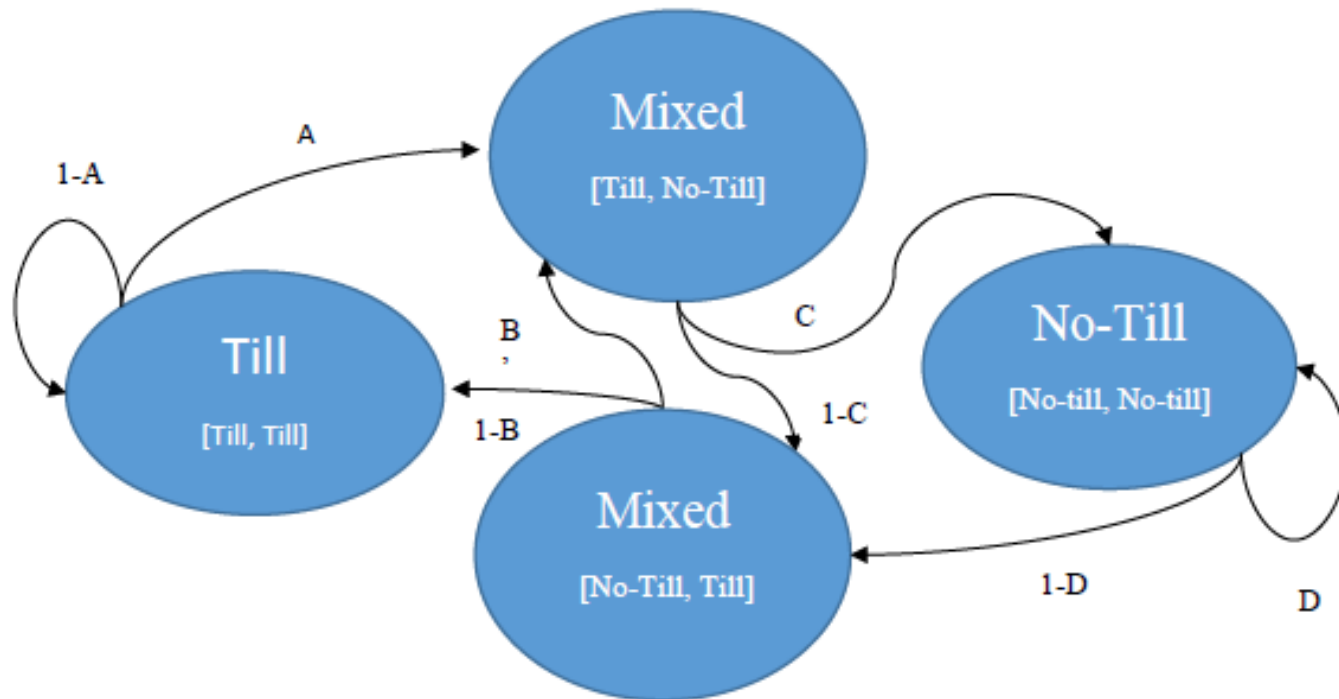
Survey	Probability of No-Till		Impact of No-Till Two Years Back
	Till -> No-Till	No-Till -> No-Till	
2010 Corn	30.40%	83.74%	53.34%
2012 Soybeans	32.32%	87.29%	54.97%
2011 Sorghum	17.53%	89.98%	72.45%
2011 Barley	45.94%	80.54%	34.60%
2013 Rice	15.00%	65.48%	50.48%
2013 Peanuts	42.60%	64.28%	21.68%

Note: These percentages are shares of fields (using survey weights) according to the farm operations table and other questions. Since fields are observed for (up to) five years, and two years are used for the information on lagged tillage decisions, there are (up to) three years of transitions observed for each field.



Schematic of a Second Order Markov Model for Tillage

With two levels of tillage, a second-order Markov model is represented by four possible two-year tillage “states” and four transition equations capturing the likelihood of transition between states. Persistence can arise from asymmetries in the transition equations.



Findings from Survey Analysis

- Persistence is a feature of No-Till across survey years (observations are “field-years”).
 - No-till: 64 – 90 %
 - Mixed tillage: 43 – 71 %
 - Till: 90 – 96 %
- Prior research suggests that about 10 to 15 percent of the cross-sectional variation is explained by soil and climate (Wade and Claassen 2017, forthcoming).



Limitation of the Survey Analysis

The main limitation of the ARMS survey for evaluating the persistence from program payments comes from three data limitations:

- Five years of tillage adoption is not sufficient time when contracts are three years.
- The survey cannot be adequately linked to data on prior program participation.
- The sample size is small given the likelihood of program participation (statistical power).

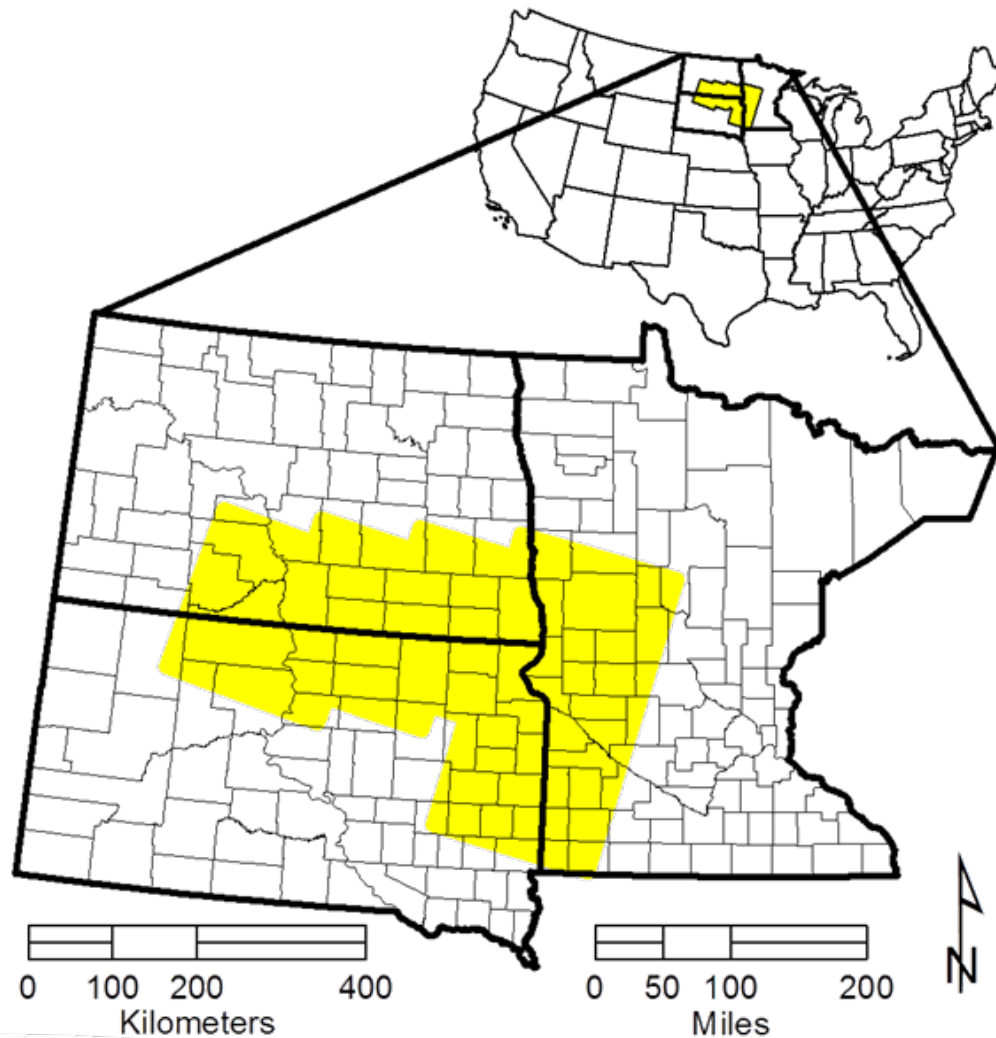


Satellite Data Solution

- USDA ARS and partners have developed methods to estimate residue from multi-spectral satellite image (Daughtry 2006)
- Residue estimates can be used to infer tillage decisions or worked with directly.
- For this project, we developed residue estimates for fields in the Northern High Plains from 2007 to 2016.



Study area focused on the boundaries between SD/ND and SD/MN – 150,000 sq km



Summary of Contracts and Residue (Percent of Field Covered)

Year	Fields with Contracts			Two-year Average Residue			
	Before	During	After	In Contract		Not in Contract	
				Mean	N	Mean	N
2007	337	99	0				
2008	264	136	8	31.60	111	31.23	246,786
2009	236	143	44	35.34	116	32.78	258,245
2010	131	151	133	37.55	120	32.18	265,533
2011	106	136	175	37.04	108	32.00	271,785
2012	73	129	229	37.82	98	34.39	275,202
2013	45	67	322				
2014	20	81	331				
2015	0	63	373	32.36	59	32.30	321,072
2016	0	13	423	43.30	10	32.54	322,283
	1212	1018	2038	35.63	622	32.50	1,960,906



Increases in Residue (%) Persist After Contracts Conclude

Variable	Contract Fields		All Fields	
	(1)	(2)	(3)	(4)
Constant	33.596 (0.345)	31.192 (0.419)	32.503 (0.000)	31.386 (0.014)
During	2.794 (0.504)	2.586 (0.578)	2.794 (0.503)	2.547 (0.502)
After	2.727 (0.514)	2.699 (0.912)	2.727 (0.514)	2.458 (0.514)
2009		3.45		1.454

Dependent variation: two-year average of estimated percent residue. All models estimated with field-level fixed effects. A Hausman test (with non-robust errors) rejects a random effects model with $p=0.001$. Robust standard errors in parentheses. Models (1) and (2) are look at change in residue on fields that have contracts. Models (3) and (4) add the comparison of non-contract fields. Models (2) and (4) add year fixed effects.



Discussion

- Survey data reveal considerable general “structural” persistence in tillage decisions.
- Satellite-based estimates show that program payments are associated with persistent (but modest) increases in residue.
- Obstacles to causal estimates of persistence from program payments include data limitations and controlling for participation endogeneity.
- Higher levels of persistence can make no-till contracts a cost-effective form of sequestration.



References

- Antle, J. M., Capalbo, S. M., Paustian, K., & Ali, M. K. (2007). *Climatic Change*, 80(1).
- Daughtry, C. S., Doraiswamy, P., Hunt, E., Stern, A., McMurtrey, J., & Prueger, J. (2006). *Soil and Tillage Research*, 91(1), 101-108.
- Ji, Y., Rabotyagov, S., & Valcu-Lisman, A. (2015). AAEA, San Francisco, California.
- Feng, H., Kurkalova, L. A., Kling, C. L., & Gassman, P. W. (2006).. *Journal of Environmental Economics and Management*, 52(2).
- Keane, M. P. (2013). *The Oxford Handbooks: Panel Data*.
- Hua, W., Hite, D., & Sohngen, B. (2005). AAEA Providence, Rhode Island.
- Wade, T., & Claassen, R. (2017). *Journal of Agricultural and Applied Economics*, 49(2).
- Wang, H., Ortiz-Bobea, A., & Chonabayashi, S. (2015). AAEA, San Francisco, California.

