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**Temporary Subsidies and Persistent Behavior:
Evidence from Conservation Tillage**

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Introduction

Can temporary incentives induce persistent behavioral changes? Extensive research on the dynamics of brand loyalty finds consistent evidence of such effects but also finds that much of the observed persistence in consumer choice is explained by factors other than “structural” persistence (Keane, 2013). In this study, we examine the evidence for persistence in the context of payments for environmental services by focusing on the example of USDA payments for the adoption no-till. Using field-level survey data on no-till adoption, we estimate tillage adoption as a second-order Markov process.

No-till crop production, in which farmers do not till their field and plant through the residue left from the prior crop, has been widely supported through USDA conservation financial assistance but has also been widely adopted by producers who have not received payments. Between 1994 and 2012, adoption of no-till crop production in the U.S. grew from 39 million acres to 96 million acres. Over that same period, USDA’s Environmental Quality Incentives Program (EQIP) provided annual payments for the adoption of no-till on about 6 million acres. Typically these payments covered three years of no-till adoption. Since fields that remain in long-run no-till have much greater environmental benefits, the extent to which any of those 6 million acres have persisted in no-till has important implications.

Several studies of crop rotation have estimated first-order Markov models (Hua, Hite, & Sohngen, 2005; Ji, Rabotyagov, & Valcu-Lisman, 2015; Wang, Ortiz-Bobea, & Chonabayashi, 2015). One recent study has applied a Markov model to tillage adoption (Tran & Kurkalova, 2016). We find evidence that tillage decisions are best modelled as a second-order Markov process. We construct our model around three states of tillage adoption: “no-till” is two years of consecutive no-till adoption, “tillage” is two years of consecutive tillage adoption (either conventional or conservation tillage), and “mixed” is alternating years of no-till and till.

Data and Summary Statistics

To capture the potential dynamics in the tillage decision, we rely on the nationally-representative, field-level phase 2 data from the USDA Agricultural Resource Management Survey (ARMS). The Phase 2 ARMS is an extensive questionnaire on production practices and costs that is administered to randomly selected fields for a set of targeted commodities. The targeted commodity varies by year. We examine the data for corn (2010), barley (2011), sorghum (2011), soybeans (2012), rice (2013), and peanuts (2013). For our purposes, the most important aspect of the survey is that each field reports on five years of crop history and tillage history.

While there are differences across the crops, the different survey years and target crops illustrate the extensive adoption of no-till in U.S. crop production (table 1). Depending upon the year and the crop, between 7 percent and 70 percent of selected fields are in no-till. Each field is in the targeted crop in the survey year, but, due to the common practice of rotating crops, in earlier years on each survey the no-till adoption rates is for a variety of crops. This creates some large differences between the survey year and earlier years for rice and peanuts. Such differences are less pronounced for the other crops.

Second Order Markov Process

To capture the potential dynamics that would allow for persistence, we estimate a Markov model of no-till adoption. One advantage of a Markov model, versus a simpler autoregressive model, is that there are more potential sources of persistence. As a second-order Markov process, the two possible tillage decisions (no-till or tillage) create four possible tillage “states” reflecting current and previous tillage decisions (figure 1). This specification implies eight transition possibilities and four equations to the Markov model.

Differences in the probability of no-till adoption across the four states illustrate the need for a second order Model (table 2). The probability of adopting no-till when the prior decisions were both tillage (column 1) ranges from 4 percent to 10 percent. However, when the prior decision was tillage preceded by no-till (column 2), the probability of adopting no-till ranges from 30 to 61 percent. Similarly dramatic differences exist between no-till adoption with the prior two decisions were tillage followed by no-till (15 to 46 percent) versus when both prior decisions were no-till (64 to 90 percent).

General Persistence

To look at persistence, we change our four-state model into a three-state model by defining a mixed-tillage state as either NT or TN. The diagonal elements of the transition probability matrix illustrate that tillage decisions exhibit a great deal of persistence (table 3). For each field, we observe up to three transitions (since the first two years of tillage constitute the initial state in a second order model). Continuous tillage is the most persistent tillage state, with 90 to 96 percent of the transitions remaining in tillage. No-till is the second most persistence state, with 65 to 90 percent of the transitions remaining in no-till. Mixed tillage is the least persistent state but still tends toward persistence with 43 to 71 percent of the transitions remaining in mixed tillage, which probably reflects a situation in which producers have a two-year crop rotation in which one of the crops is no-till and the other is tilled.

Conclusions and Future Extensions

General persistence does not necessarily imply that temporary subsidies for no-till will induce persistent change in tillage behavior. Much of the persistence observed across the tillage states may result from cross-sectional (and persistent) variation in the underlying incentives to adopt no-till. Preliminary analysis of these tillage sequences suggest that the designation of fields as highly erodible (HEL) increases the probability of transition from conventional tillage into mixed tillage and from mixed tillage into no-till. Other important cross-sectional sources of persistence are soil, climate, and farmer characteristics. Future analysis will examine the impact of time varying covariates on transitions between states.

This research presents an important step forward in expanding our understanding of the relationship between government programs and persistent behavior. With improved data and richer empirical modeling, this examination of conservation tillage contributes to a much larger literature on habit formation (Dyner, 2000; Pollak, 1970). This research also helps in offering a model with which to predict whether recent reductions in conservation program payments for no-

till adoption (due to shifts to other practices such as cover crops) may lead to eventual declines in no-till.

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Table 1: Share of Fields in No-Till by Year across Phase 2 ARMS Surveys

	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 its) 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.

Table 2: Probability of No-Till Adoption Given Two-year Tillage History

Survey	Prior Two-Years of Tillage			
	TT	NT	TN	NN
2010 Corn	5.66%	51.55%	30.40%	83.74%
2012 Soybeans	6.85%	60.64%	32.32%	87.29%
2011 Sorghum	9.90%	30.20%	17.53%	89.98%
2011 Barley	7.01%	35.34%	45.94%	80.54%
2013 Rice	3.94%	55.03%	15.00%	65.48%
2013 Peanuts	4.64%	37.28%	42.60%	64.28%

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. TT: two years of tillage. NT: a year of no-till following by a year with tillage. TN: a year of tillage followed by a year of no-till. NN: two years of no-till.

Table 3: Probability of Persistence in Second-Order (Two-Year) Tillage States

Survey	No-Till	Mixed	Till
Corn 2010	83.7%	61.2%	94.3%
Soybeans 2012	87.3%	63.8%	93.2%
Sorghum 2011	90.0%	43.0%	90.1%
Barley 2011	80.5%	44.2%	93.0%
Peanuts 2013	64.3%	46.9%	95.4%
Rice 2013	65.5%	71.2%	96.1%

Figure 1: Transition probability equations for a model with two-year states.

