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Farmers and Habits:

The Challenge of Identifying the Sources of Persistence in Tillage Decisions

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Abstract

A number of government programs, including USDA conservation programs, provide financial incentives to entice changes in behavior. An important question for these programs is whether temporary payments can lead to persistent behavioral changes. Over the past 20 years, the USDA Environmental Quality Incentives Program (EQIP) has provided more than $250 million to farmers adopting no-till crop production. In contrast to conventional tillage, which turns over the soil prior to planting, no-till can produce a number of environmental goods such as soil carbon sequestration, especially if farmers adopt no-till continuously for a long time period. This study examines whether temporary no-till payments result in persistent adoption of no-till beyond the term of conservation contracts. In the first part of our analysis, we examine field-level survey data, model no-till adoption as a second-order Markov process, and establish that in general there is considerable persistence in farmers' tillage decisions. In the second part of our analysis, we examine a unique dataset of satellite-based estimates of field-level residue estimates in the Northern High Plains and examine changes in residue before, during, and after enrollment in EQIP. We conclude by discussing the potential implications of persistence for program outcomes as well as the challenges in identifying the mechanisms driving persistence.

Can temporary incentives induce persistent behavioral changes? Government programs often use temporary subsidies to incentivize behavioral changes, and the persistence of those changes

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can have large implications for policy outcomes. Persistent effects of temporary incentives also have implications for private sector decisions and are receiving increasing attention within behavioral economics. For example, research on the dynamics of brand loyalty finds 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 U.S. Department of Agriculture (USDA) payments for the adoption of no-till.

The USDA working lands conservation programs – the Environmental Quality Incentives Program (EQIP), the Conservation Stewardship Program (CSP), and several other smaller programs – provide over $2 billion per year in payments to farms who agree to adopt conservation practices on eligible land. A large share of these programs involves financial assistance to farmers who adopt specific management practices each year during a defined contract period. Many EQIP no-till contracts span three-years. Program participants are typically not under any obligation to continue using those practices after their contracts are closed out. No-till has been one of the most prevalent practices over EQIP's 20 year history, and over the life of the program USDA has obligated over $250 million toward no-till.[i]

Conventional tillage involves plowing (i.e.: "tilling") fields prior to planting a crop in order to mechanically control weeds, incorporate nutrients, or otherwise prepare the seed bed for planting. Farmers engaged in no-till will plant through the residue left from the prior crop. USDA conservation programs have supported no-till (as well as reduced tillage) due to the many environmental benefits that are associated with the practice, including reduced soil erosion, reduced fertilizer usage, and increased soil carbon. While EQIP and other programs have heavily encouraged no-till adoption, many farmers have adopted no-till without receiving conservation program payments because there can be significant on-farm benefits such as reduced fuel costs. Between 1990 and 2012, adoption of no-till crop production in the U.S. grew from 20 million acres to 96 million acres. Over that same period, EQIP provided annual payments for the adoption of no-till on over 4 million acres. Typically these payments covered three years of no-till adoption.

In this study, we examine evidence for the overall persistence of no-till crop production. We also examine whether temporary no-till payments result in persistent adoption of no-till beyond the term of conservation contracts. We conduct this study in two parts in order to use complementary information from different datasets. First, using field-level survey data that provide good information on tillage sequences but poor information on prior program participation, we estimate tillage adoption as a second-order Markov process. This allows us to estimate overall persistence. Second, to examine the impact of program participation on persistence, we combine a novel dataset on satellite-based residue estimates (a proxy for tillage decisions) with administrative data from the EQIP program to estimate the persistence of changes in on-field residue following the completion of EQIP contracts.

In our analysis of the survey data, we find evidence that tillage decisions can be modelled as a second-order Markov process. Across a variety of crops, we find that tillage decisions are persistent. This is a novel finding in the literature on tillage adoption. We also use satellite-based residue estimates combined with EQIP program data to investigate the impact of no-till payments, and find evidence that residue levels rise during EQIP contracts then remain near those levels after the contracts conclude. Since higher residue is only a proxy for no-till adoption, this provides indirect evidence of post-contract persistence in no-till.

This research advances our understanding of the relationship between government programs and persistent behavior, which is critical to evaluating program impacts and to designing future programs. Our results do not directly identify the mechanisms for this persistence, and different mechanisms would imply the need for different incentive structures to encourage no-till adoption. Possible mechanisms for an impact of the EQIP program on no-till persistence include overcoming annual (static) marginal costs or up-front conversion costs, or contributing to human capital and learning. The latter may have important behavior underpinnings that are difficult to distinguish from knowledge accumulation and habit formation. As one farmer stated in a recent New York Times article on no-till adoption, “One of the toughest things about learning how to do no-till is having to unlearn all of the things that you thought were true” (Goode, 2015). Our hope is that this preliminary evidence demonstrating persistence in no-till will inspire future contributions--through improved data development and rich modeling—to the larger literature on habit formation (Dynan, 2000; Pollak, 1970).

Literature

Much of the literature on tillage adoption utilizes cross-sectional data and, therefore, uses static models. This approach reflects the common methodology in most of the conservation practices adoption and program evaluation (additionality) literature. These static models reveal several important aspects about the incentives underlying conservation tillage adoption.

No-till adoption in the U.S. has increased from about 20 million acres in 1990 (CTIC, cited in Hill 1998) to about 96 million acres in 2012 (NASS, 2014). Soil characteristics are found to be one of the most consistent variables correlated with no-till adoption. Many studies find that farmers are much more likely to adopt no-till on highly erodible land (HEL) (Ding, Schoengold, & Tadesse, 2009; Prokopy, *et al.*, 2008; Wade & Claassen, 2017). An important explanation for this is that no-till can be used to meet conservation compliance provisions that require farmers to adopt soil conservation practices on HEL to retain eligibility for a variety of USDA program payments (Wade & Claassen, 2017). Weather and climate can also impact adoption, although some studies find statistically insignificant relationships (Ding et al., 2009; Kurkalova, Kling, & Zhao, 2006). Many other studies examine variables such as farmer characteristics related to human capital (Featherstone & Goodwin, 1993; Wu & Babcock, 1998), and farm size or land tenure (Soule, 2001; Soule, Tegene, & Wiebe, 2000). The literature also provides some evidence that tillage is a field-level rather than a farm-level decision. For example, about 15 percent of corn acres in 2010 and 2011 were on farms that adopted no-till on some but not all of those corn acreage, and a similar share of soybean acres were also on farms that mixed tillage types for the crop (Wade, Claassen, & Wallander, 2015). A recent meta-analysis (Baumgart-Getz, Prokopy, & Floress, 2012) and literature reviews (Carlisle, 2016; Prokopy et al., 2008) discuss a range of other drivers of the tillage decision.

Bringing the behavior of tillage adoption into the context of conservation program impacts requires studies that carefully construct counterfactual estimates of program impacts. To evaluate what is termed "additionality," these studies must compare farmers who receive financial assistance to adopt no-till to a control group of farmers who do not receive financial assistance. This allows the researchers to estimate the likelihood that program participants would have adopted no-till even without payments. The share of those participants that would have been likely to adopt without payments represents non-additional tillage adoption. Studies estimate that conservation tillage payments are only about 47 percent additional (Claassen, Duquette, & Smith, 2018)

Most of the studies on tillage have not dealt with the dynamics of tillage decisions, but some of the dynamics of the tillage decision were evident early in the expansion of no-till adoption. Statistical analysis of selected Midwestern counties in the 1990's showed that no-till was more likely to be used with soybeans than with corn within soybean-corn rotations (Hill, 1998). Further data collection revealed considerable spatial variation in long-run patterns of tillage adoption, with large shares of fields in some counties adopting continuous no-till and relatively few fields in other counties (Hill, 2001). In a study of cross-sectional data on tillage adoption, one of the strongest predictors of no-till adoption was no-till adoption in the prior year (Banerjee, *et al.*, 2009). While some studies have looked at dynamic impacts on soil carbon (Conant, *et al.*, 2007) and long-run sequences of adoption (Wade & Claassen, 2015), only one recent study truly modeled tillage as a dynamic decision by incorporating a first order Markov model (Tran & Kurkalova, 2016). This dynamic approach is more common when looking at crop rotation decisions, where a number of studies have estimated first-order Markov models (Hua, Hite, & Sohngen, 2005; Ji, Rabotyagov, & Valcu-Lisman, 2015; Wang, Ortiz-Bobea, & Chonabayashi, 2015). Related literature estimates dynamic crop choice using a Markov chain approach with farm-level data (Aurbacher & Dabbert, 2011) and estimates land use transitions and crop choice using a Markov model applied to survey data (Hua et al., 2005). Given the links between cropping and tillage decisions, some of the dynamics that characterize the cropping decision are also likely to be present in the tillage decision.

Outside of the literature on tillage and cropping decisions, there are many studies looking at the economics of habit formation and the persistence of spending patterns or specific economic decisions. Persistence has been observed in recreations demand (Adamowicz, 1994), aggregate beef demand (Holt & Goodwin, 1997), food calorie consumption (Richards, Patterson,

& Tegene, 2007), brand choice (Erdem, 1996) and tobacco use (Labeaga, 1999). From a theoretical standpoint, much of this work is built on dynamics in consumer preferences (Pollak, 1970), although some research is built on investment in durables by producers (Rozen and Wolpin 1993) or the role of human capital and learning (Foster & Rosenzweig, 1995). Importantly, cross-sectional and time-series analysis will, perhaps not surprisingly, yield very different results (Heien & Durham, 1991).

In the context of paying farmers for no-till, understanding dynamic patterns of behavior (such as additionality and persistence) matters for evaluating the social welfare implications of programs such as EQIP. These behavioral patterns directly impact the dynamic production function for the public benefit being considered. There are a number of potential public benefits associated with no-till adoption, including improved air and water quality, and carbon sequestration. Since no-till adoption is closely associated with use of herbicide tolerate seeds, there may also be some costs to the public, such as increased herbicide use and the associated increase in herbicide resistant (Fernandez-Cornejo, *et al.*, 2013). In the case of carbon sequestration, dynamic considerations are important because carbon stored in the soil today could be released tomorrow if management practices change, for example if a farmer were to till following several years of no-till. Therefore, the degree to which carbon sequestration through no-till is *permanent* relates directly to the issue of persistence and the structure of programs that provide financial incentives for such practices. In the economic literature, hypothetical payment schemes for carbon sequestration in agricultural soils are generally structured in a couple of ways. First, you could pay farmers to change their practices and accumulate and/or store carbon over an extended period of time in order to ensure at least some degree of persistence and permanence. For example, Antle, Capalbo, Paustian, and Ali (2007) and Feng, Kurkalova, Kling, and Gassman (2006) assume that carbon contracts would need to be long-term. Or, you could discount the value paid in the short-term to account for the uncertainty associated with carbon permanence and/or concerns about whether the benefit is additional, or consider it a temporary credit. Murray, Sohngen, and Ross (2007) summarize some of these options in the context of carbon project accounting, and discuss their economic implications.

Empirical Framework

In order to test our research hypothesis—that temporary incentive payments can induce persistent behavioral changes—we need an empirical framework that allows for persistent behavior but does not assume it. We begin by exploring how dynamics might enter into a basic model where demand for tillage as an input is derived from a field-level, single-period, profit-maximization decision. We then apply the potential outcomes framework to incorporate the impact of program participation into our model. Lastly, we introduce a model of tillage as a second-order Markov model, which has the advantage of providing several pathways for persistence.

Field-level tillage demand

Most papers on no-till adoption assume that a farmer is maximizing profit on a single field by choosing crop, tillage, and a set of variable inputs that includes fertilizer, labor, fuel, herbicides and pesticides, and perhaps irrigation water. Under standard assumptions regarding the production function, this maximization problem results in a set of conditional input demand functions, including for tillage. The ability to substitute between inputs is critical for no-till. One of the most common arguments used to promote no-till among producers is that it will increase profits by saving farmers time, fuel, and fertilizer.

There are four basic ways in which the profit of a given field could include dynamics related to the tillage decision: dynamic benefits, dynamic costs, partially sunk capital costs with uncertainty about future returns, or fully sunk human capital (learning) costs.

Dynamic benefits could arise through benefits that depend upon improvements in soil health. One reason that soil scientists study continuous no-till adoption is that it can take decades for no-till to result in a new equilibrium of soil structure, chemistry, and ecology. This implies that the marginal benefits of no-till adoption are not constant over time and likely depend upon the history of tillage on a given field. Herbicide resistant weeds may pose a significant challenge in maintaining continuous no-till.

Dynamic costs could arise from weed pressure. Since one of the purposes of conventional tillage is weed control, there is some concern that continuous no-till increases weed pressure, although there may be other management options that mitigate this, such as increased use of herbicide or adoption of winter cover crops.

In terms of capital costs, shifting to no-till adoption (at the farm level) requires investment in new planters and possibly other machinery that is tailored to working the field in the presence of greater crop residue. This equipment can represent a large fixed cost. When this fixed cost is paired with uncertainty over future returns and is not fully recoverable, farmers would value the option of either waiting to adopt no-till or staying in no-till.

Finally, an important aspect of no-till adoption that gets a great deal of attention in the literature is the role of learning and human capital. Many farmers have written describing how no-till adoption changed the way they farm, and frequently these testimonials note that it took them several years to learn how to properly time planting, herbicide, and fertilizer applications, and other operations on the field; how to properly change levels of other inputs; and how to adjust and manage new equipment.

Potential Outcomes Framework

Because the tillage decision is the outcome of interest (y_t), we focus on evaluating the impact of program participation, which we model as a binary treatment (D_t) where D_t = 1 implies participation in a current contract. We will treat tillage as a binary variable and assign the outcomes using letters (1 = no-till (*N*), 0 = tillage (T)). (We will use the letter designations to help with interpreting tillage sequences later in the modeling framework.) Many studies have used the potential outcomes framework, typically with propensity score matching methods, to estimate the average treatment effect on the treated (ATT) of program participation on tillage adoption: ($ATT = E(y_t = 1|D_t = 1) - E(y_t = 1|D_t = 0)$ (Claassen et al., 2018; Claassen, Horowitz, Duquette, & Ueda, 2014; Mezzatesta, Newburn, & Woodward, 2013; Pufahl & Weiss, 2009). The challenge in estimating the treatment effect comes from the need to construct the second expectation since the same individuals (fields) cannot simultaneously be participating in the program and not-participating in the program.

Adjusting this framework to look at persistence requires lagging the treatment variable. For any post-participation period tillage adoption decision, the average treatment effect estimator becomes ($ATT = E(y_t = 1|D_{s<t} = 1, D_t = 0\ ) - E(y_t = 1|D_{s<t} = 0, D_t = 0)$. One plausible candidate for an estimate of the second expectation, which we use in our analysis, is the pre-treatment period for the treated observations.

One issue with this framework is the absence of a true dynamic framework for examining persistence over a longer period of time. This approach raises the question of which years following treatment are the subject of interest, and whether those years can provide valid inference about longer-term persistence. One solution to this limitation is to collect data over very long periods following treatment and simply use the maximum extent of persistence estimates available when conducting policy analysis. Another solution, which we explore below, is to look for a modeling approach that directly incorporates persistence as a feature of the tillage decision and allows for program participation to either directly or indirectly change the underlying drivers of persistence.

Dynamics and a Second Order Markov Model

The approaches to modeling no-till described above either assume away persistence or place strict assumptions on the nature of persistent behavior. Single-period models clearly assume persistence away entirely. Any variable that has a positive marginal effect on no-till adoption (such as a conservation program payment), will, by construction, only have a "temporary" effect. While such a modeling approach is often taken due to data limitations, the tillage demand function estimated by such models implies, perhaps incorrectly, that policies designed to induce long-run adoption of no-till must provide the equivalent of long-run (persistent) incentives.

An alternative approach, using lagged tillage decisions in an autoregressive model of tillage adoption, allows for some persistence. However, it still implies that the effects of any temporary subsidy will themselves be temporary, as the tillage demand will eventually return to the pre-subsidy equilibrium.

At the opposite end of the spectrum, many agronomic field studies and integrated agronomic-economic simulation studies often compare continuous conventional tillage to continuous conventional no-till adoption over very long time periods, sometimes over multiple decades. To incorporate behavior and profit maximization in these models requires a rather strong assumption that farmers essentially make a "permanent" tillage decision. In addition, the length of time over which these studies define continuous adoption can vary widely. Policy studies often choose the length of a typical management contracts (three to five years). Soil studies often define continuous no-till over a time frame long enough for soil characteristics to achieve equilibrium (multiple decades). One limitation of this approach is that fixing a long time period as the definition of "continuous" no-till increases the difficulty of determining when farmers have switched into or out of continuous no-till. Even at the low-end of definitions of continuous tillage (three years), this would require at least six years of data and would only reveal clear switching for farmers who switch in the fourth year. The difficulty of clearly defining and observing continuous adoption of a practice is a major reason to consider the use of a Markov model.

Markov models have been widely used in studies of brand preference, where consumers face repeated choices over a fixed choice set (Keane, 2013). For no-till, we chose a second order Markov model based on patterns observed in the data. The mechanics of implementing this model require defining tillage "states" that capture lagged information about prior tillage decisions.

Using a two-year definition of the tillage state, there are four possible tillage states: TT (00), TN (01), NT (10), and NN (11). The memory in the definition of the tillage states means that the transitions between states are limited (figure 1). The core of our empirical framework involves estimating the conditional transition probabilities.

These transition probabilities can be captured with a system of four binary choice equations. At any point in time, a given field is in one for the four states and has a likelihood of adopting no-till represented by one of these equations (equations 1A to 1D).

$$A: \quad P(Y_{it} = 1 | YL2_{it} = 00) = \mu_A + f_A(X_{it})$$

$$B: \quad P(Y_{it} = 1 | YL2_{it} = 01) = \mu_B + f_B(X_{it})$$

$$C: \quad P(Y_{it} = 1 | YL2_{it} = 10) = \mu_C + f_C(X_{it})$$

$$D: \quad P(Y_{it} = 1 | YL2_{it} = 11) = \mu_D + f_D(X_{it})$$

There are two sources of persistence in this system of equations. The innate persistence is given by the first terms in each equation. If conventional tillage is innately persistent, then μ_A will be near zero. This implies that without considerable "stimulus" from a change in X_{it}, a field in two years of conventional tillage is very unlikely to adopt no-till. Similarly, if no-till is innately persistent, then μ_D will be near one. Persistence in a mixed tillage state would occur if μ_B be close to zero and μ_C be close to one. We will examine this source of persistence in the first part of our analysis.

The other source of persistence in this system of equations is covariate persistence, or what we might call incentive asymmetry. If a covariate has a strong impact in one conditional probability and not another, it can either induce persistence or mitigate (dampen) persistence. For example, suppose that an increase in energy prices encourages no-till adoption by farms engaged in conventional tillage but doesn't impact no-till decisions by other farmers. (So high energy prices are the "gateway" to no-till). A temporary shock of high energy prices could then push fields into no-till. Such asymmetric movement between states is observed in a variety of settings, such as the “rockets and feathers” models of oil and gasoline price movements, which are also adapted Markov models.

Pre-Analysis of General Tillage Persistence with Survey Data

To examine persistence in no-till adoption we examine data from a field-survey of production practices. After describing the data, we explain how we construct a sequence of two-year tillage “states” from the five year tillage sequence reported in the data. We then present evidence that the transition between tillage states is best represented as a second-order Markov process. We conclude by evaluating the general levels of persistence observed in the data.

Field-level Survey Data

To incorporate these potential dynamics into 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 cropping and tillage history.

While there are differences across crops, the different survey years and target crops clearly show the extensive adoption of no-till in U.S. crop production (table 1). 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 we observe no-till adoption rates for a variety of crops. Depending upon the year and the crop, between 7 percent and 70 percent of selected fields are in no-till (table 1).

Tillage Sequence and Two-year Tillage States

For this research, we construct a five-year tillage sequence for each field using information from several survey questions. Since 2009, ARMS Phase 2 has included a four-year crop history table that collects information about the prior crops planted on that field. Up through the 2013 survey, for each crop the farmer was also asked to indicate (with a binary response) whether that field was no-tilled. In 2015, the tillage question was modified to ask farmers whether they adopted either no-till or strip-tillage on the field (as a single, combined category). (Note: there was no Phase 2 survey in 2014.)

In addition to the prior tillage type reported in the crop history table, farmers are asked very detailed questions about machinery operations relating to the planting of the target crop in the survey year. This provides reliable, detailed information about the farmer's tillage decision on that field. In combination with the crop-history this provides a four-and-a-half year sequence of tillage. (Note: we will treat it as a five year sequence, but we will have incomplete information in the first year for farms that double-cropped.)

Since we model no-till as a second-order stochastic process, we require essentially two lags of tillage adoption decisions. This means that we have up to three usable observations for fields that provide a usable tillage response in all five years. Since farms report up to 2 crops in a year, we only code a field as no-till if both crops are indicated as no-till. If a farm only plants a single crop, we use the tillage code for that crop.

Some of the excluded fields have no information on tillage in those years when their prior crop history was missing. This could occur for a number of reasons, such as when the farmer surveyed wasn't operating the field in those years. Some of the excluded fields report that they left the field fallow and didn't grow a crop in a given year. For those years, all of the data are coded as zeroes (indicating tillage) due to data cleaning protocols that filled in missing values as zeroes. We don't believe that fallow fields are likely to be tilled, but we know anecdotally (from trade literature and blogs) that some farms will till during fallow rotations to control weeds or to encourage deeper moisture infiltration. Since we don't trust the current zeros for fallowed fields and don't want to code all fallow fields as no-till, we exclude fallow years from the analysis.

Second Order Markov Process

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 allow for persistence in all tillage states, 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 persistent 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.

Satellite Data Analysis

To examine the impact of program payments on persistence, we constructed a dataset that would allow us to identify EQIP contracts for no-till and observe their tillage decisions following their contract completion. Post-contract data on tillage adoption was developed through use of newly developed algorithms to estimate residue, a proxy for tillage decisions, from satellite estimates.

Study Area and Administrative Data

We develop a unique dataset in order to examine the impact of EQIP program participation on no-till persistence. For this portion of the analysis, we focus on a 150,000 km^2 study area in the Northern Plains, which covers parts of the states of North Dakota, South Dakota, and Minnesota. We focus on this region due to a high level of observed variation in the funding of EQIP no-till contracts across these states during the period of our study, 2007 to 2016. Both North Dakota and Minnesota have funded many EQIP contracts with no-till practices, but South Dakota has almost entirely avoided including the no-till practice on EQIP contracts. Data on EQIP program participation, including the timing and location of no-till contracts, were drawn from the USDA Natural Resources Conservation Service ProTracts database.

Although we know that fields that had an EQIP contract for the no-till practice were engaged in no-till during the duration of the contract, the database contains no information about tillage practices prior to or post-contract. We can assume that fields that enter into a no-till contract were not engaged in no-till in the preceding period since the program does not provide financial assistance for practices that have already been adopted. However, as we will discuss below, it is not certain that these fields were using conventional tillage and may have practiced reduced tillage or possibly have been in a mixed till/no-till states.

Residue Estimates

In order to evaluate the impact of the no-till contracts on farmer behavior after the contract period, we develop a dependent variable from satellite data that is a proxy for the farmer's tillage decision: estimated residue (from the prior crop) ideally after all spring operations are completed, including planting, to capture the minimum residue value. When farmers use conventional tillage, the residue that was left after harvest of the preceding crop is turned into the soil and very little residue remains on the surface of the field. In contrast, under no-till production, essentially all of the remaining residue is left on the surface, thus observed residue prior to new crop green-up is a good proxy for the tillage decision. Of course the actual residue level can reflect a variety of other management decisions (e.g.: harvesting of stover or straw or other residue from the prior crop, use of a winter cover crop, etc.) and so the correspondence between residue and tillage is not perfect.

Following an established literature that develops the Normalized Difference Tillage Index (NDTI) for this purpose (C. S. Daughtry et al., 2006), we compiled imagery from Landsat 5 and 7 (2007-2012) and Landsat 7 and 8 (2014-2016) to create a dataset of images between April and

June that would capture the planting period for most fields in the study region. Landsat imagery is publicly available via the USGS Earth Explorer website (https://earthexplorer.usgs.gov).

Since the algorithms used to estimate residue can vary based on the preceding crop, our analysis requires fields that represent unique crops. The polygons used as the units of analysis for this study were developed by evaluating crop history patterns based on the USDA NASS cropland data layer (Johnson & Mueller, 2010). The polygons were also buffered and filtered so as to minimize the effects of field borders, water bodies, and road and rail networks. This methodology minimized some issues presented by using the administrative field boundaries or other potential units of analysis for residue estimation, since a single administrative field may have been strip cropped, split into sub-fields, or otherwise have changed over time with respect to how the land was cropped.

The Landsat images were masked to control for clouds and shadows, as well as wet soils, which impact NDTI estimation (C. S. Daughtry et al., 2006). Wet soils, defined as more than 3mm of rain in the two days prior to a satellite overpass, were identified by using NEXRAD 4 km Rainfall Data (National Weather Service; http://water.weather.gov/precip/download.php). We also masked cropland with growing vegetation, as indicated by a Normalized Difference Vegetation Index (NDVI) of greater than 0.3, as suggested by C. Daughtry, Hunt, Doraiswamy, and McMurtrey (2005). Finally, we estimate NDTI, and translate NDTI into residue estimates using conversion equations that related the NDTI value to residue cover percentages based upon the prior crop residue type (corn or soybeans).

Given our earlier finding in the survey data that tillage can be modelled as a second order Markov process captured through two-year tillage states, we create two-year averages of the residue estimates. Fields in mixed tillage that may be oscillating between higher and lower residue values will therefore have an average two-year residue estimate, a more accurate representation of their tillage state. Due to this averaging, we are not able to calculate a two-year tillage state for 2007, the first year of the analysis. In addition, there was not sufficient satellite data in 2013 to make any residue estimates, so we also lack two-year estimates for 2013 and 2014.

Findings on Persistence in Residue Changes

To analyze the impact of program participation on tillage, we estimate an unbalanced panel model of the residue on the average field during and after contract enrollment. There is considerable variation across years in the number of fields with before-, during- or after-contract exposure, although there are more after contract observations because EQIP has gradually reduced funding of no-till across all states since enrollment in that practice peaked in about 2009 and 2010 (table 4, columns 1-3). There is also variation in the dependent level; average residue levels fluctuate across years both in no-till contract fields and for fields that do not have contracts (table 4, columns 4 and 6). Some of this variation is likely due to weather or poor satellite coverage.

To compare during and after contract periods, we begin by looking only at fields that have a no-till EQIP contract at some point over the study period (table 5). We used a fixed effects model to control for unobserved field characteristics such as slope, soil-type, highly erodible land designation, and other factors that might be correlated with estimated residue and program participation. A Hausman test rejects a random effects specification. We estimate the model with and without year fixed effects to control for regional weather and price shocks. We find that for these fields, the average residue during the before contract period is 33.6 percent without the year dummies and 31.2 percent (base year of 2008) with the year dummies. Relative to those baselines, the two-year average residue estimate increases by an average of 2.8 percentage points without year dummies and 2.6 percentage points with year dummies. These changes are highly statistically significant, suggesting that there is a behavioral change due to the contracts. However, this is considerably less than the average change in residue typically associated with no-till, which could be due to the fact that the baseline residue levels are relative high. One possibility is that prior to participating in a no-till contract many of these fields are engaged in reduced tillage rather than conventional tillage.

After contract completion, these fields have residue levels that are still significantly higher than the baseline (pre-contract) levels. Relative to the pre-contract baseline, post-contract residue is 2.7 percentage points higher in both models. This suggests fairly high levels of persistence beyond the completion of the contracts.

For a second version of these models, we include all no-contract fields. This has a small impact on the differences between the baseline period and the during- and after-contract periods, but the overall result remains the same.

Discussion

The above analysis shows that temporary payments for no-till adoption could lead to some persistent adoption of no-till beyond the contract. In this section we discuss the strengths and limitations of the evidence presented above. We conduct a simple sensitivity analysis of how persistence could impact benefit cost assessment of soil carbon sequestration through no-till contracts. We explore the implications of persistence for program design. Lastly, we discuss the challenges involved in trying to design future studies to provide causal estimates of programs on persistent behavior in this context.

Assessment of Existing Evidence

While a number of prior studies on conservation tillage have examined either adoption of continuous no-till or estimated simple auto-regressive models, we are not aware of any studies that explicitly model no-till persistence. Some earlier research studied the dynamics of crop choice, which is closely related to the tillage decision, but the question of long-run impacts from temporary changes in incentives is not generally considered or modelled.

In our analysis of survey data, we found that persistence is a general property of the tillage decision, which we model as a second-order Markov process. There appear to be some differences in persistence between the three tillage states: no-till, mixed-tillage, and tillage, which could suggest important asymmetries in conversion costs between states. However, there are a variety of other possible explanations for this "structural" persistence. Unobserved field-level and farm-level characteristics could drive cross-sectional variation in the underlying incentives to adopt each of the three tillage states, and so the structural persistence estimated above is likely larger than the persistence that would be associated with temporary shocks to those incentives, such as conservation program payments. If the research on no-till persistence follows the lines of research on persistence in consumer brand loyalty, then it is likely researchers will find that there is less persistence due to temporary shocks to farmer incentives after controlling for other explanations (Keane, 2013).

To examine the impact of conservation program payments on persistence, we turned to data on field-level residue. We found that both during-contract and after-contract residue levels are, on average, higher than pre-contract residue levels. More importantly, there is small difference between during-contract and after-contract levels, even after controlling for average trends in residue among program participants and non-participants within the study region. Given that program participation is voluntary, future research could lead to different estimates of persistence if there is significant endogeneity bias due to correlation between the program participation decision and unobserved factors that also influence persistence. Nonetheless, these results suggest that the general persistence observed in the survey data does translate to the impact of program participation.

Implications for Costs of Carbon Sequestration

As discussed above there are many public benefits (e.g.: reduced erosion) and some public costs (e.g.: increased herbicide use) that are associated with increased adoption of no-till. Of these, the benefit that is most tied to persistence is soil carbon sequestration. The following empirical exercise shows how important no-till persistence can be to the outcome of a benefit/cost test for soil carbon sequestration within the structure of conservation programs like EQIP.

To the extent that a farmer engages in no-till after the conclusion of a conservation contract that includes no-till, the effective benefit-cost ratio of the program can change dramatically. We construct a simple example to illustrate how the persistence of the no-till practice combines with other important behavioral parameters to influence the average cost of carbon sequestration within such a program. To construct this exercise we need five parameters: the average per acre payment in the program, the number of years of payments, the amount of soil carbon sequestered over the long-run (assuming permanent adoption of no-till), the share of payments that result in additional adoption of no-till, and the share of additional payments that shift into permanent adoption due to the persistence effect.

For the program design, we assume that all contracts are three year contracts and that the average per acre payment is the current EQIP payment rate of $23 per acre. We also consider higher and lower payment rates. The lower payments could either reflect actually lower payments or could reflect the share of total benefits that comes from soil carbon sequestration.

For the amount of soil carbon sequestered we use a mid-point value of the amount of carbon sequestered based on 20 years of no-till adoption relative to a baseline of conventional tillage (Sperow, 2016). We also consider a lower level of sequestration, which could arise if program participants are instead shifting from reduced tillage into no-till. The fairly low changes in residue observed in our High Plains analysis suggest that this might be a more realistic assumption. We implicitly assume that there is zero long-run carbon sequestration on contracts that only temporarily shift into no-till.

For the additionality parameter we choose the main result of 47 percent from (Claassen et al., 2018). We then look at three levels of persistence by assuming that either 10, 50 or 80 percent of the additional adoption will be effectively continuous or "permanent" adoption. Given the underlying behavior, there is likely to be a correlation between additionality and persistence.

Based on these parameters, we calculate the implied average cost of sequestering a ton of carbon via no-till through the EQIP program as follows:

$$Average\ Cost\ Carbon = \frac{Payment * Years}{Carbon\ sequestered\ * Additionality * Permanence}$$

By taking the overall average for this stylized carbon sequestration program, this approach essentially acknowledges that there are behavioral obstacles to effectively targeting with voluntary abatement programs.

This exercise shows that under an EQIP-like design ($23 per acre for 3 years), current additional estimates, and average sequestration estimates, the average cost of carbon sequestered would be below the social cost of carbon of $36 per ton of carbon dioxide equivalent in 2015 (EPA, 2016). Lower permanence levels are not able to clear this threshold (table 6). While we observe fairly large persistence in the above analyses, these levels of persistence will tend to translate into lower estimates of permanence. For example, even in a standard Markov model with high persistence, the permanence (the likelihood of a field staying in no-till for twenty years (the minimum time period implied by our carbon sequestration numbers)) would be well below the average year-to-year persistence (the likelihood of staying in the no-till state for one year).

Implications for Program Design

The presence of persistence has a number of implications for program design. First, persistence implies that farmers' hurdle rates for adopting no-till will be declining over time. At a minimum this suggests that programs that design contracts such that the per-acre payments decline over the life of a contract could be more cost-effective that the current approach of using a fixed annual payment. Depending upon the mechanism driving persistence, this could also imply that one-time payments that help cover conversion costs could be more effective and possibly more cost-effective than annual payments.

If human capital accumulation and/or habit formation are important drivers of persistence, then other efforts to promote no-till adoption could be highly effective. This would likely include programs with agricultural extension or conservation education components. To a certain extent, this would imply that education-based promotion of no-till is an important substitute for financial assistance through conservation programs. However, there are also likely to be important complementarities between these programs. If development of human capital is a form of conversion costs between tillage states, then investment in education programs could reduce the hurdle rates that financial assistance programs are facing when trying to induce voluntary adoption of no-till.

Challenges of Studying Programs and Persistence

Future research on persistence in conservation practice adoption will face a number of important challenge in developing improved estimates of the causal impacts of program participation. Some of the challenges arise in any effort to study persistence and some are unique to studying field-level production decisions.

Data limitation are one of the primary obstacles to studying persistence. As we have shown above, compiling data on post-contract practice adoption is a non-trivial challenge. In addition comparable data are needed for both program participants and non-participants. While existing surveys provide one avenue for such data, obtaining enough observations on program participants would require over-sampling prior participants. The desired time frame for studying persistence is also a challenge. One on hand, the difficulty of constructing long-term panel data sets is not unique to agriculture and has already been addressed in some studies in education and health care. The added complication in this setting is that we consider tillage to be a field level decision, but in long-term panels, the operator (decision maker) on a given field may change over time due to changes in land ownership or rental agreements, among others.

The second major obstacle to studying the persistence effect of program participation is controlling for the voluntary nature of program participation. In addition to the various econometric methods for addressing this problem, there are at least two related improvements that could be made in data collection and program implementation. The first improvement would be to collect outcome data (tillage decisions) for fields that are rejected by the program due to the funding constraints. A second, and related improvement, would be to randomly assign contracts when the program is budget constrained. (The current system uses a contract scoring and ranking system.)

Lastly, distinguishing between the important mechanisms of persistence is an important topic for future research. This will likely require additional data collection to look for changes in behavior and preferences. For conversion costs, researchers would need to know the existing level of capital stock (e.g.: tractors and planters) of farmers as well as having panel data on changes in that stock. There may be ways to exploit the Markov model framework to look for changes in sensitivity to marginal incentives (e.g.: fuel prices and weather) before and after contract participation. Studying changes in human capital and clearly identifying the mechanisms of learning and habit formation is likely to be much more difficult.

Conclusion

In this study, we have looked at the extent to which persistence is a feature of no-till adoption and examined whether there is persistence of no-till adoption following the conclusion of EQIP contracts. We found that persistence is a general feature of no-till adoption. We also found that changes in on-field residue associated with EQIP no-till contracts in the Northern Plains persist after the end of those contracts. Future research is needed to provide causal estimates of persistence. The current findings show that persistence has important implications for conservation program outcomes.

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) 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 Conditional on Two-year Tillage History

		Prior Two-Years of Tillage					
		TT	NT	Second Order Difference	TN	NN	Second Order Difference
2010 Corn	N (field-years)	5,108	493		515	1,815	
	Share in No-Till	5.66%	51.55%	+45.89%	30.40%	83.74%	+53.34%
	Unique Fields	1,851	451		423	735	
2012 Soybeans	N (field-years)	3,573	587		481	2,442	
	Share in No-Till	6.85%	60.64%	+53.79%	32.32%	87.29%	+54.97%
	Unique Fields	1,326	458		431	932	
2011 Sorghum	N (field-years)	595	215		92	717	
	Share in No-Till	9.90%	30.20%	+20.30%	17.53%	89.98%	+72.45%
	Unique Fields	258	185		90	275	
2011 Barley	N (field-years)	2,166	315		227	1,042	
	Share in No-Till	7.01%	35.34%	+28.33%	45.94%	80.54%	+34.60%
	Unique Fields	818	274		209	419	
2013 Rice	N (field-years)	1,277	160		202	257	
	Share in No-Till	3.94%	55.03%	+51.09%	15.00%	65.48%	+50.48%
	Unique Fields	466	148		147	113	
2013 Peanuts	N (field-years)	845	106		90	289	
	Share in No-Till	4.64%	37.28%	+32.64%	42.60%	64.28%	+21.68%
	Unique Fields	322	99		83	129	

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%

Note: These percentages are shares of fields (using survey weights) according to the farm operations table and other questions. Persistence in No-Till is three years of no-till. Persistence in Mixed tillage is a sequence of either till—no-till—till or no-till—till—no-till. Persistence in Till is three years of till.

Table 4: No-Till EQIP Contracts and Estimated Residue in Northern High Plains

	Fields with Contracts			Two-year Average Residue			
				In Contract		Not in Contract	
Year	Before	During	After	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

Fields in these statistics are polygons created based on the USDA NASS cropland data layer and do not represent administrative fields. Contract fields are those fields which were either corn or soybeans in the prior year (a constraint from the residue estimate methods) and overlay the administrative fields that contained an EQIP contract for no-till. Residue estimates are in percentage of field covered by residue based on analysis of multiple satellite images prior to spring planting. To reflect the two-year states supported by the Markov model applied to survey data, these residue estimates are two year averages. There are no estimates for 2013 due to insufficient satellite imagery. There are no estimates for 2007 and 2014 due to missing estimates in the preceding years.

Table 5: Additional Residue During and After EQIP No-Till Contracts

	Contract Fields		All Fields	
Variable	(1)	(2)	(3)	(4)
Constant	33.596	31.192	32.503	31.386
	(0.345)	(0.419)	(0.000)	(0.014)
During	2.794	2.586	2.794	2.547
	(0.504)	(0.578)	(0.503)	(0.502)
After	2.727	2.699	2.727	2.458
	(0.514)	(0.912)	(0.514)	(0.514)
2009		3.45		1.454
		(0.444)		(0.015)
2010		4.117		0.942
		(0.577)		(0.020)
2011		3.103		0.825
		(0.647)		(0.020)
2012		3.936		3.193
		(0.753)		(0.022)
2015		-0.081		0.621
		(0.840)		(0.021)
2016		3.118		0.813
		(0.933)		(0.022)
N	2547	2547	1961528	1961528
N_g	436	436	3.40E+05	3.40E+05
r2	0.022	0.081	0	0.019
F	18.058	26.856	18.114	4816.523
corr	-0.077	-0.054	0.003	-0.009

Dependent variation: two-year average of estimated percent residue. All models estimated with field-level fixed effect. A Hausman test (with non-robust errors) rejects a random effects model with p=0.001. Robust standard errors in parentheses.

Table 6: Simulated Impacts of Persistence on Effective Cost of Soil Carbon Sequestration

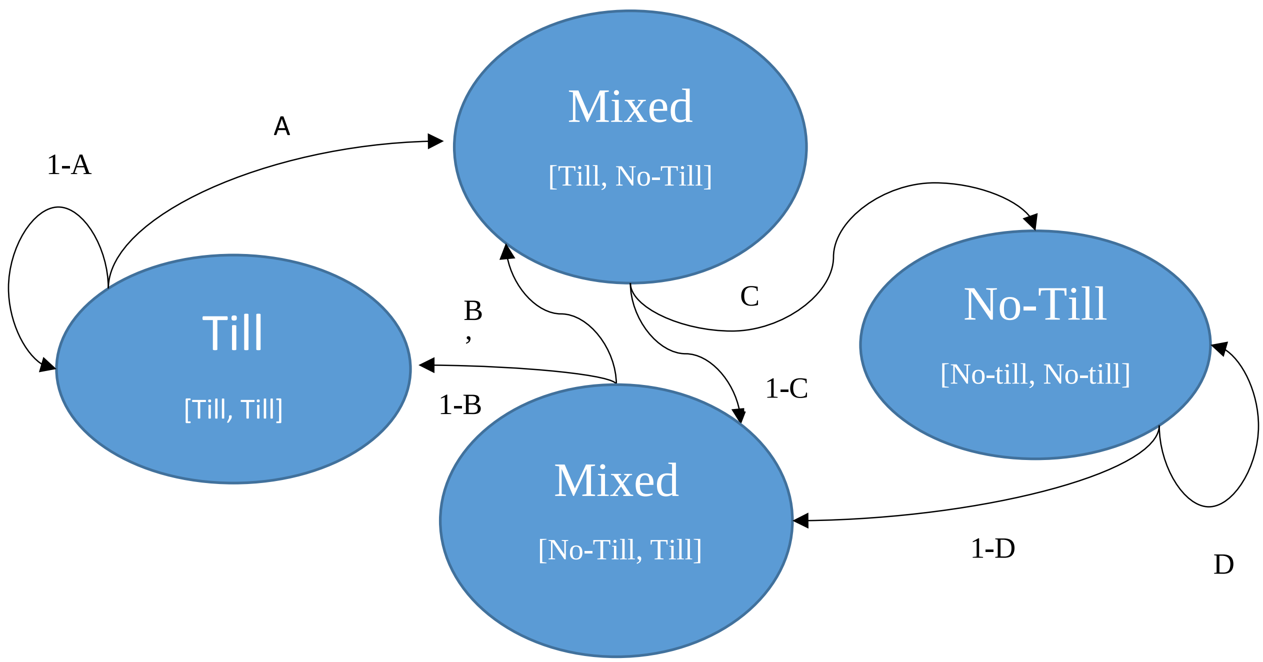
Conventional to No-Till Conversion Scenario				
CO_2 sequestered		25.67		
Additionality		47%		
		Annual Payment Per Acre		
Permanence		$15	$23	$40
	10%	**$37.30**	$57.19	$99.46
	50%	**$7.46**	**$11.44**	**$19.89**
	80%	**$4.66**	**$7.15**	**$12.43**

Reducted-till to No-Till Conversion Scenario				
CO_2 sequestered		7.19		
Additionality		47%		
		Annual Payment Per Acre		
Permanence		$15	$23	$40
	10%	$133.16	$204.18	$355.10
	50%	**$26.63**	$40.84	$71.02
	80%	**$16.65**	**$25.52**	$44.39

Values are in dollars per ton of carbon dioxide equivalent. Bold values are below the EPA (2016) estimate of the social cost of carbon for 2016.

Figures

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



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[i] Author's calculation from USDA administrative data. There are $14.4 million in obligations for no-till on 1997 to 2002 fiscal year EQIP contracts in the FSA data from the early years of the program. There are $251.0 dollars in obligations for no-till in the 2002 to 2016 fiscal year EQIP contracts in the NRCS ProTracts. There may be as much as $3.7 million dollars in overlap between the two databases in 2002, and a few of the years in the database include practices in some other conservation programs.