The Impact of No-Till on Agricultural Land Values in the US Midwest

Le Chen, North Carolina State University, lchen28@ncsu.edu

Roderick Rejesus, North Carolina State University, rmrejesu@ncsu.edu

Serkan Aglasan, Mehmet Akif Ersoy University, serkanaglasan@gmail.com

Stephen Hagen, Dagan Inc., Applied Geosolutions, steve@dagainc.com

William Salas, Dagan Inc., Applied Geosolutions, wsalas@appliedgeosolutions.com

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Abstract

This study investigates the impact of no-till practice on agricultural land values in the United States (US) Midwest. Two county-level panel data sets - the agricultural census farmland value data and the Iowa Farmland Values Survey data - are separately merged with a novel satellite-based data set on no-till adoption rates to achieve the study objective. Based on linear fixed effect econometric models, recently developed "external-instrument-free" estimation procedures, and a number of robustness checks, we find that increasing no-till adoption rates has a statistically significant positive effect on agricultural land values at the county-level. Results from the empirical analysis support the notion that economic and environmental benefits from adopting soil conservation practices, such as no-till, are capitalized into higher farmland values.

Keywords: No-Till, Agricultural Land Values, Fixed Effects, Panel Data
JEL Codes: Q15, Q18, Q28, Q52

1 Introduction

Agricultural land plays a unique and important role in agriculture. Farm real estate, including land and the structures on it, accounts for over 82% of United States (US) farm-sector assets in 2016 (Burns et al., 2018). Protecting agricultural land enables long-term agricultural production security for farmers and provides essential environmental benefits to society. Agricultural land values are generally determined by, among other factors, expectations of future income, which are themselves related to the productive capacity of the soil and expected economic returns from agricultural production (Borchers et al., 2014; Reydon et al., 2014; Telles et al., 2016, 2018). Hence, soil quality and fertility levels affect farmland values, either through the rental rate or the sale price (or assessed value) of the farmland.[1] On the other hand, continuous exposure to erosion makes soils progressively less productive, as it damages soil structure and degrades organic matter and nutrients (Zuazo and Pleguezuelo, 2009; Lee et al., 2021). This productivity decline, in turn, reduces the land's capacity to produce food and therefore affects economic returns from agricultural production. Thus, adoption of soil conservation practices, which improves soil quality and minimizes damage and costs associated with soil erosion, is typically viewed as an important and positive contributor to agricultural land value (King and Sinden, 1988). However, empirical evidence on this issue has been limited (Boyle, 2006; Kik et al., 2021). Understanding the relationship between agricultural land values and the use of soil conservation management practices is critical to quantifying the full benefits of adopting these soil conservation practices.

In the US, one of the most widely used soil conservation strategies is the use of no-tillage (or the no-till) practice (Islam and Reeder, 2014; Wade et al., 2015). Conventional tillage has traditionally been used by farmers worldwide to prepare the soil for planting, control weeds, incorporate manure or fertilizer in the soil, and mix crop residue into the soil. However, conventionally tilled soils are disturbed more, typically absorb more heat, and

[1]Please note that we interchangeably use the term "agricultural land" and "farmland" in this study. These terms are considered one and the same in this study.

warm up more quickly, which in turn accelerates surface runoff and soil erosion (Claassen et al., 2018). In contrast, no-till is a soil management practice that reduces soil-disturbing agricultural activities. Even though no-till requires special equipment (e.g., disc seeders or no-till drills to make furrows, immediately plant seeds, firm them, and cover the soil), with this practice, the soil suffers from minimum disturbance, and crop residues are left on the soil surface, allowing for coverage and protection of the soil from erosion and compaction. This enhances the capacity of the soil to maintain organic matter for longer periods (Arshad et al., 1990; Helgason et al., 2010; Aziz et al., 2013; Karlen et al., 1994). Through the continued application of this conservation practice, soils on farmland can potentially become more stable (i.e., enhancing sustainability), reduce negative environmental externalities from agriculture (e.g., nutrient runoff), and improve overall productivity of agricultural systems (Aziz et al., 2009; Lafond et al., 2011; Blanco-Canqui and Ruis, 2018; Cusser et al., 2020). Enhanced farmland productivity can in turn positively influence agricultural land values.

The objective of this study is to examine the impact of no-till adoption on agricultural land values in the US Midwest. To achieve this objective, we mainly utilize two publicly available county-level agricultural land value data sets (each separately merged with data on no-till adoption and other control variables). The first panel data set is from the census of agriculture (AgCensus) collected by the US Department of Agriculture National Agricultural Statistics Service (USDA-NASS) for census years 2007, 2012 and 2017. The second data source is from the Iowa Farmland Values Survey conducted yearly by the Iowa State University Center for Agricultural and Rural Development (ISU-CARD) from 2005 to 2016, for all counties in Iowa. Agricultural land values are at the county-level and are measured in nominal dollars per acre ($/acre) for both data sets. A unique satellite-based data that have information on county-level no-till adoption are then drawn from the Operational Tillage Information System (OpTIS) database. This data set covers counties from twelve Midwestern states for the period 2005-2018. The census of agriculture and Iowa State University farmland values data sets are then separately merged with the OpTIS data and other relevant variables from other sources (e.g., weather variables, soil quality measures, agricultural returns, federal government payments, and county population estimates). Based on these two merged panel data sets, we develop linear fixed effect econometric models to empirically analyze how no-till practice adoption rates affect agricultural land values. This estimation strategy allows us to address endogeneity due to time-invariant unobservables and to better identify the effects of no-till on agricultural land values. In addition, we utilize estimation procedures developed by Lewbel (2012) and Krauth (2016) that do not require external instrumental variables (IVs) satisfying classical exclusion restrictions. These recently developed procedures allow us to deal with potential endogeneity caused by unobservables that vary over time and across counties (i.e., not just time-invariant unobservables).

Due to the potential effects of improved soil quality on agricultural land values, there is now a large literature investigating the relationship between soil erosion and farmland values, as well as the relationship between soil conservation management practices (in general) and farmland values (see, among others, Miranowski and Hammes, 1984; Ervin and Mill, 1985; King and Sinden, 1988; Nielsen et al., 1989; Milham, 1994; Bakker et al., 2005; Boyle, 2006; Kik et al., 2021). Much of the existing literature examine these types of relationships using hedonic models or they focus on the investment values of soil conservation management in general. For example, King and Sinden (1988) investigated the relationship between on-farm soil conservation efforts and farmland value by applying the hedonic approach in an Australian farmland market context. They then determined whether and by how much changes in soil conservation affect land prices, ultimately finding that soil conservation efforts positively influences land prices. Gardner and Barrows (1985) applied a linear hedonic price function to examine whether past soil control investments influence farmland values, and in contrast to King and Sinden (1988), finds that investments in soil conservation are not capitalized into farmland values. Even in light of this past literature that examine the effects of soil conservation efforts (in general) on agricultural land values, there has been a limited number of studies that investigated how no-till adoption (in particular) affect farmland values. One example is a study by Telles et al. (2018), where they examined the relationship between no-till adoption and the value of agricultural lands in Brazil using simple (non-regression-based) descriptive analysis. They showed that agricultural lands under no-till tend to have higher values relative to lands under other soil management systems.

Our study contributes to the literature in a couple of ways. First, to the best of our knowledge, there has been no study that econometrically examined the impact of no-till on county-level agricultural land values in the US Midwest. By determining the effects of no-till adoption on agricultural land values, this study provides empirical evidence on whether the potential productivity and environmental benefits of the no-till practice also translates to increases in agricultural land values. An improvement in agricultural land values can be viewed as an "additional" benefit from no-till adoption (on top of other economic and environmental benefits it provides). The farmland value effect of no-till has not been previously documented in the context of agricultural production in the US Midwest.

Second, we also make a contribution to the literature by providing inferences based on two unique farmland value panel data sets combined with a novel satellite-based data on no-till adoption. The use of these two panel data sets allow us to examine the impact of no-till on agricultural land values over a wider geographical region and over a longer time period compared to previous studies. In addition, given the geographic scope of the data sets, we produce new insights as to the aggregate county-level effects of no-till adoption on agricultural land values in a major agricultural producing region of the US rather than estimating effects only for a specific location. Implementing the empirical analysis on two farmland value data sets also allow for validating the robustness of our results.

Moreover, as already mentioned above, the panel nature of the data gives us the opportunity to better account for potential endogeneity due to time invariant factors (e.g., unobserved management ability, topographical features of the county, and soil features), and in turn more accurately estimate the impact of no-till on farmland values. Our use of new "external-instrument-free" estimation approaches also allows us to address potential endogeneity due to time- and county-varying unobservables without needing external IVs that satisfy classical exclusion restritions.[2] One of the difficulties in estimating a credibly identified effect of no-till on agricultural land values is the likely effect of unobserved confounding factors that vary over time and across counties. For example, unobserved soil conservation investments at the county-level (e.g., conservation crop rotation) or unobserved county-level adoption of herbicide-tolerant varieties (both of which can vary over time and across counties) may be positively correlated with no-till adoption and farmland values (Perry et al., 2016; Claassen et al., 2018), thereby causing endogeneity issues. Hence, the use of recently developed external-IV-free models allow us to address residual endogeneity not accounted for by the the traditional linear fixed effect model.

Findings from our study show that using no-till has a strong and statistically significant positive impact on agricultural land values. Higher no-till adoption rates increases county-level farmland values. For counties in the twelve US states included in the USDA-NASS AgCensus dataset, our empirical analysis suggest that a 1% increase in no-till adoption rate leads to an increase of $7.86 per acre in agricultural land value. On the other hand, based on data from the Iowa Farmland Values Survey, our study indicate that a 1% increase in no-till adoption rate increases agricultural land values by $14.75 per acre in Iowa counties. These results suggest that the use of no-till soil conservation practice can positively contribute to higher agricultural land values through improved soil quality.

2 Background: No-till and Agricultural Land Values

No-till is a soil conservation technique that do not disturb the soil as is done in conventional tillage (Claassen et al., 2018). No-till is a farming practice in which the seeds are directly

[2] Note that endogeneity issues due to time-county-varying unobservables are traditionally addressed using IV approaches such as two-stage least squares (2SLS). However these traditional IV approaches require external IVs that satisfy exclusion restrictions (i.e., IV is correlated with the endogenous variable, but uncorrelated with the error terms). Unfortunately, we believe that there are no available strong external IVs that satisfy these exclusion restrictions, which is the reason why we opted to use new external-IV-free approaches.

deposited into untilled soil that has retained the previous crop's residues (Claassen et al., 2018). No-till has been found to simultaneously reduce the erosive force of water runoff and increase the ability of the ground to hold onto soil particles, making this approach remarkably effective at curbing soil erosion (Karlen et al., 1994; Lee et al., 2021). Furthermore, no-till production also fosters the diversity of soil flora and fauna by providing a richer habitat for beneficial soil organisms (Schmidt et al., 2018). Therefore, the use of no-till also encourages soils to develop a more stable internal structure, further improving its overall capacity to productively grow crops and to buffer them against stresses caused by farming operations or environmental hazards (Reganold, 2008; Ogle et al., 2012).

Notwithstanding the numerous studies that have shown generally positive soil health and productivity effects of no-till, it is important to note that there is still debate as to the whether no-till is indeed advantageous to soil health and crop yields under all environmental conditions (Ogle et al., 2012; Pittelkow et al., 2015; Cusser et al., 2020). For example, based on agronomic studies conducted in the 1990s and 2000s, no-till has been viewed by many as a way to increase soil carbon, quality, and function, and reduce carbon dioxide emissions (see, among others, Karlen et al., 1994; Kladivko, 2001; Six et al., 2004). However, there has also been a number of recent studies that have questioned whether no-till actually increases soil organic carbon and decreases carbon emissions (Ogle et al., 2012; Powlson et al., 2014). Numerous studies have also shown that no-till adoption is associated with lower yields, although there are also a number of studies that have demonstrated no-change or increases in yields (Ogle et al., 2012; Pittelkow et al., 2015). Many of these studies recognize that heterogeneity in conditions contribute to the contrasting yield effects of no-till (i.e., with yield increases more often observed in water-limited conditions, and declines more often seen in cool and wet conditions, or poorly drained soils) (Pittelkow et al., 2015). A recent study by Cusser et al. (2020) also suggests that conflicting soil health and productivity findings in past no-till studies perhaps stem from the use short-term agronomic data, and more longer term studies tend to have more consistent sustainability findings for no-till (Six et al., 2004).

Following the contrasting agronomic findings on the soil health and yield effects of no-till, there is also little consensus as to the impact of no-till adoption on overall farm profitability. The no-till practice has been shown to offer some private economic advantages to farmers themselves. First, no-till typically requires 50-80% less fuel, and 30-50% less labor as compared to conventional tillage-based production (Claassen et al., 2018). Hence, no-till is often perceived as contributing to significant decreases in agricultural production costs. Second, although specialized no-till seeding equipment is sometimes needed, running and maintaining other tillage equipment is not necessary, typically lowering the total capital and operating costs of machinery required for crop establishment by up to 50% (Reganold, 2008; Telles et al., 2018). In spite of these private benefits, there are cases where upfront machinery investments and increased herbicide cost of controlling weeds exceeds short-term input cost savings from no-till (Cusser et al., 2020). Therefore, the economic literature on no-till generally indicate that the profitability of no-till is variable and site-specific, depending on such factors as soil characteristics, local climatic conditions, cropping patterns, and other attributes of the farming operation (Rejesus et al., 2021).

Even though there is uncertainty surrounding economic benefits from no-till vis-a-vis short-term adoption costs, based on the 2017 AgCensus data, 37% of reported acres in the US were under no-till, which include both continuous no-till and rotational no-till (i.e., rotational no-till refers to using no till after one crop, but tilling after another crop in the rotation). Total no-till acres reported in 2017 was 104 million acres, which is about 8 million acres higher than what was reported in the 2012 AgCensus. The region with the largest amount of no-till acres are in the Great Plains, with Kansas and Nebraska each having more than 10 million of reported no-till acres, and the Dakotas and Montana having around 8 million no-till acres each. Iowa also had more than 8 million acres of no-till in 2017. Figure 1 shows the percent and total acres in each state under no-till in 2017 (Zulauf and Brown, 2019). Worldwide, the US ranks first among all countries with regards to no-till adoption.

Despite the relatively strong no-till adoption levels in the US relative to other countries, there have been continued interest in factors affecting adoption of no-till and the potential barriers to adoption (outside of direct economic considerations). Wade and Claassen (2017), in their review of the literature, find that the no-till adoption decision in the US is generally influenced by soil characteristics, climate, farm characteristics, producer demographics, and region or location variables. In particular, soil characteristics like soil erodibility and drainage, as well as climate variables, play an important role in sustained adoption of no-till (Wade and Claassen, 2017). Perry et al. (2016) indicate that no-till is a complement to adoption of herbicide tolerant varieties. Social and attitudinal factors, such as lack of information and reluctance to change, as well as inappropriate design of government support programs, have also been found to hinder adoption of no-till practices (Rodriguez et al., 2009). Understanding factors affecting no-till adoption is critical to better design policies that aim to encourage further uptake of this practice.[3]

Agricultural land values, on the other hand, are determined by a complex set of farm and nonfarm factors, including farm agricultural productivity characteristics, external economic and governmental influences, and buyer or seller's characteristics (Dunford et al., 1985; Drescher et al., 2001). However, the principal determinant of agricultural land values is the ability to generate future returns. According to relevant farmland valuation studies, the common capitalization formula is expressed as the relationship between current farmland values and expected returns in future periods (Borchers et al., 2014; Ifft et al., 2015; Sant'Anna et al., 2021). The capitalization formula is expressed as:

$$L_t = \sum_{n=1}^{\infty} \frac{E_t(R_{t+n})}{\prod_{j=1}^{n}(1 + r_j)}, \tag{1}$$

where L_t is agricultural land values, $E_t(R_{t+n})$ is the expected net economic returns in period $t + n$, and r_j is the discount factor. Traditional studies use rents or economic returns to

[3]As suggested by a referee, it is important for us as researchers to also understand factors affecting no-till. Some of these factors are likely unobservable and may also indirectly affect agricultural land values. If so, then these unobservables can cause endogeneity problems in our empirical model. Hence, we use knowledge about these unobservable factors to properly specify our empirical model and to use appropriate estimation procedures. For example, we used weather variables as controls to account for climate factors, and also use linear fixed effects models to account for unobservable soil features that are roughly time-invariant.

agricultural production as a measure of expected returns, but a number of studies expand the definition to include potential returns for conversion to higher valued land use activities, such as residential or commercial use (Goodwin et al., 2003) and government payments (Weersink et al., 1999; Ifft et al., 2015), or the net returns from a soil conservation investment (Ervin and Mill, 1985). Specifically, Ervin and Mill (1985) define the present value of net returns from a conservation practice investment as:

$$PV_t = \sum_{n=1}^{\infty} \frac{E_t(B_{t+n} - C_{t+n})}{\prod_{j=1}^{n}(1 + r_j)}, \tag{2}$$

where PV_t is present value of the change in net returns of the conservation practice investment, B_{t+n} is benefits of conservation practice, and C_{t+n} is costs of conservation practice. Therefore, adoption of a practice (e.g., no-till) yields a specific flow of B's and C's over time, and therefore affects the expected future economic returns of farmland. Despite this key insight, there has been no study that have empirically shown whether or not benefits from no-till are capitalized into farmland values.

3 Data Sources and Empirical Approach

3.1 Data Sources and Summary Statistics

The data used in this study are collected from a variety of sources. The main dependent variable of interest is a measure of county-level agricultural land value (in nominal $/acre). We utilize two county-level data sets as the main sources of information for farmland values (and each farmland data set is then separately merged with data on no-till adoption and other control variables). The first land value data set is from the USDA-NASS census of agriculture conducted in the following years: 2007, 2012, and 2017. Farmers are asked to estimate the current market value of the surveyed parcel that he or she operates. The census of agriculture is carried out to provide stakeholders a detailed snapshot of the status of US farms and ranches every five years. It is the leading source of uniform and comprehensive agricultural data for every state and county in the US. The market value of land reported in the census of agriculture is measured as of December 31 of the census year.

The second source of farmland value data is from the Iowa Farmland Values Survey conducted yearly by ISU-CARD from 2005 to 2016. The survey is an expert opinion survey based on reports by licensed real estate brokers, farm managers, appraisers, agricultural lenders, county assessors, and selected individuals considered to be knowledgeable of land market conditions (Zhang et al., 2020). Participants in the survey are asked to estimate the value of high-, medium-, and low-quality land in their county. This survey is the only data source that provides publicly available annual farmland value estimates at the county-level for each of the 99 counties in Iowa. Agricultural land values are reported at the county-level and are measured in $/acre.

We include these two unique county-level farmland value datasets as there are several major distinctions between the ISU survey data and USDA census data. First, the respondents are different: ISU survey relies on land market expert opinions, while USDA census survey relies on estimates by individual agricultural producers. Second, the farmland value definitions are different: USDA uses surveyed farmer's self-reported estimate of the current market value of the land that they operate, while the ISU survey asks for an estimate of the typical farmland value for an average-sized farms in a particular county from their respondents. Last, the timing of reporting for each survey is different: ISU provides an annual agricultural land value estimate at the county level, while the USDA census of agriculture is conducted every five years. Additionally, it is important to note that there are differences between agricultural land value estimates based on surveys and those based on actual agricultural land transaction prices. Farmland value surveys provide a good indication of the direction of change and level of value, but they are still an opinion survey that represents who is being surveyed. Survey estimates are usually higher than transaction prices. For example, according to Stinn and Duffy (2012), ISU survey results were consistently (80% of the time) higher than sales prices, by an average of 8.9%.

After collecting farmland value data, we then gathered information for our main independent variable of interest - county-level no-till adoption rates.[4] We utilize satellite-based county-level data on no-till adoption rates from the Operational Tillage Informational System (OpTIS) database developed by Dagan Inc.®, Applied Geosolutions (AGS) (now ReGrow Ag®).[5] OpTIS provides satellite-based information on usage trends of agricultural conservation practices (i.e., like no-till and reduced till practices) over large agricultural areas. OpTIS produces accurate, timely and spatially comprehensive annual data of no-till adoption using information from multiple earth-observing satellites. Data from satellites are used to assess residue levels in the field and the OpTIS system classifies them into four categories: very low (0-15%), low (16-30%), moderate (31-50%), and high (51-100%). No-till adoption is then generally attached to fields classified as high residue, reduced till adoption to low and moderate residue, and conventional till to very low residue.

The OpTIS data are calculated and validated at the farm-field scale, but the privacy of individual producers is fully protected by reporting only spatially-aggregated results at much larger scales (Hagen et al., 2020). Moreover, validation of the OpTIS no-till adoption data was mainly done through comparisons with photo and roadside survey information collected at the field level for several representative counties (See Hagen et al. (2020) for more details on the validation procedure). In their validation analysis of the OpTIS data (relative to 827 observed fields over the twelve states covered), Hagen et al. (2020) suggest that the remote-sensing based OpTIS data for residue cover only had a 4.3% difference relative to the field observed data. The Pearson's correlation coefficient between OpTIS-estimated residue cover and field estimated residue cover is 0.683.

[4]Please note that the farmland value data sets were separately merged with the no-till adoption data set at the county-year level. The control variables were then merged in at the county-year level as well. This process allowed us to create the panel data sets used in the empirical analysis.

[5]Dagan Inc.® AGS, a geospatial analysis company (now ReGrow Ag®) , partnered with the Conservation Technology Information Center (CTIC) to create OpTIS and generate satellite imagery of back dated no-till adoption going back to 2005. This effort was funded by USDA, Monsanto, John Deere, Soil Health Partnership, Indiana Soybean Alliance and Indiana Corn Marketing Council. Please note that the county-level OpTIS data used in the study are proprietary and are not publicly available. Hence, researchers interested in using the county-level data should formally request for access from ReGrow Ag®.

Despite the reasonable accuracy levels of the OpTIS tillage data (based on comparisons with field data), it is important to note that there are still known discrepancies between the OpTIS-estimated no-till acres vis-à-vis other aggregate no-till data sets (i.e., like those from the census of agriculture) (Hagen et al., 2020).[6] The differences in the tillage adoption estimates between the OpTIS and census of agriculture data likely stems from the different methods used to collect the data. For example, the census of agriculture relies on surveys of the complete census of growers and likely captures their intent to use no-till, and whether they indeed adopted no-till at the time of the survey. Therefore, it can happen that a farmer indicated that he/she used (or intended to use) no-till and this is recorded in the census of agriculture as adoption. But it is possible that satellites only observe less than 50% residue cover. In this case, OpTIS will not register as no-till adoption, while the census will. Nonetheless, even in light of these potential discrepancies, Hagen et al. (2020) find that the OpTIS data is still highly correlated with the no-till data from the census of agriculture with an 80% correlation coefficient. The validity of the OpTIS data is also supported by the fact that it has been used in recently published research articles in agricultural economics (See, for example, Chen et al. (2021)).

The county-level OpTIS data on no-till adoption rates covers 645 counties over twelve states in the US Midwest (Appendix Figure A1). OpTIS data is available for all counties in the following states: Illinois, Indiana, and Iowa (i.e., complete statewide coverage). However, the OpTIS data only have partial coverage for the following nine states: Kansas, Michigan, Minnesota, Missouri, Nebraska, Ohio, Oklahoma, South Dakota, and Wisconsin (i.e., not all counties in these states have OpTIS data). In addition, the OpTIS no-till data we utilized covers the time period from 2005 to 2018. A crop year in OpTIS is from November 1 of the previous year through October 31 of the current year (i.e., the 2005 crop year extends from

[6]The county-level no-till adoption data from the AgCensus were not utilized in the study because of the limited number of years these data were available. For example, the cover crop and no-till adoption data from the census were only available in 2012 and 2017. Moreover, at the time of this study, only the AgCensus data in 2017 were available at the county-level. The lowest level of aggregation available for the 2012 census data was at the state-level.

November 1, 2004 through October 31, 2005). The timing of the no-till adoption data is for the months after the harvest of the row crop from the previous year and before planting of the subsequent cash crop. For example, the OpTIS cover crop adoption data in crop year 2015 reflects cover crop detected by the satellites starting in November 2004, after the harvest of the cash crop in the Fall of 2004. For this study, we utilize information on no-till adoption area after production of any of the following cash crops: corn, soybeans, small grains, and other cash crops.

In addition to data on agricultural land values and no-till adoption rates, we also utilize weather variables, soil quality variables, agricultural production returns, government payments, and county population data collected from a variety of sources to estimate regressions that represent the spirit of the capitalization formulas in equations (1) and (2). The weather data are collected from the Parameter-Elevation Regression on Independent Slopes Model (PRISM) climate dataset. PRISM dataset is recognized world-wide as one of the highest-quality spatial climate data sets currently available and is the USDA official climatological data. The relevant weather variables utilized in the study include: the number of growing degree days (8-29°C) and heating degree days (above 29°C), precipitation, and precipitation squared (Schlenker and Roberts, 2009). All degree days and precipitation used in this analysis are accumulated over the growing season months from May to September. On the other hand, the soil quality data used in the study are drawn from the POLARIS database (Chaney et al., 2016). POLARIS is essentially a map of soil series probabilities that has been produced for the contiguous US at a 30m spatial resolution. It provides a spatially continuous, internally consistent, quantitative prediction of soil series. The specific soil quality variables we utilize in this study are soil pH, the percentage of soil organic matter, and the available water content. County-level estimates of crop production returns are collected from the US Bureau of Economic Analysis (BEA). We define farmland agricultural returns as crop receipts less crop-related expenses (e.g., seed, fertilizer and labor) . Lastly, county-level government payments and population estimates are also obtained from the BEA. The government payments variable consist of deficiency payments under price support programs (for specific commodities), disaster payments, conservation payments, and direct payments to farmers under federal appropriations legislation. We include weather, soil quality, agricultural production returns, government payments, and population variables as controls in our specification since environmental conditions, crop production returns, government payment, and population level in each county vary over time and can influence agricultural land values (more on this below).

Brief descriptions of the variables utilized in this study, as well as the corresponding summary statistics, are presented in Table 1. The average agricultural land values from the census of agriculture for the twelve states covered in the OpTIS data is \$4525.36 per acre (for the census years 2007, 2012, and 2017), while the average farmland value for all the counties Iowa is \$5862.94 per acre over the period 2005-2016. The mean no-till adoption rate for counties in the twelve OpTIS states is 27.55%, and for counties in Iowa it is 26.80%. Graphs of the year-to-year variations (and trends) for the county-level agricultural land values and no-till adoption rates are reported in Appendix Figure A2 for the agriculture-census-based data set, and in Appendix Figure A3 for the Iowa county-level farmland value data.[7]

3.2 Empirical Specification and Estimation Strategy

To determine the impact of no-till adoption on agricultural land values, we utilize the main empirical specification defined as follows:

$$L_{it} = \theta NT_{it} + \beta \mathbf{X}_{it} + \eta t + \gamma_i + \varepsilon_{it} \tag{3}$$

where L_{it} denotes agricultural land values (in nominal \$/acre) in county i at time t, NT_{it} represents the percentage of cropland acres using the no-till practice for county i in year t, t is a linear time trend, γ_i are the county fixed effects, and ε_{it} is the error term.

[7] In Appendix Figure A4, we also present the average yearly no-till adoption rates for the full OpTIS data from 2005 to 2018. The mean no-till adoption percentage for the full county-level OpTIS data from 2005-2018 is 29.06%. Moreover, we present detailed maps of no-till adoption rates and agricultural land values for both panel data sets in Appendix Figures A5 to A8.

The vector $\mathbf{X}_{it}$ accounts for a number of control variables such as weather, productive capacity of the soil, agricultural production returns, government payment, and population level. Including these $\mathbf{X}_{it}$ variables in the specification allows us to control for other observable county- and time-varying factors that can influence agricultural land values. As mentioned above, we use the following weather variables in the specification: number of growing degree days (8-29°C) and heating degree days (above 29°C), precipitation, and precipitation squared. These are the typical variables utilized in the climate change economics literature and accounts for how climate/weather influences agricultural land values (Ortiz-Bobea, 2020). Soil quality factors are included in the specification to account for the inherent productive capacity of the land, and the variables we use include: soil pH, the percentage of soil organic matter, and available water content of soil. These variables are commonly-used soil quality measures that serve to represent (or proxy for) the degree of soil quality (or soil productivity), which in turn can influence agricultural land values (Miranowski and Hammes, 1984). Agricultural returns is included since it directly influence farmland values. In addition, having agricultural returns in the specification help to control for other unobserved time-county-varying factors affecting productivity, such as yields, fertilizer application levels, or labor share. We also include county-level federal government payment levels in the specification, as farmlands that receive more direct government payments tend to have higher returns that are embodied in the capitalization formula (Goodwin et al., 2003). In addition, total population of each county is also included in $\mathbf{X}_{it}$ to control for the effect of urbanization pressures on agricultural land values. All of these control variables are commonly used to account for agricultural and nonagricultural factors affecting farmland values in the agricultural land value capitalization literature (Ifft et al., 2015; Drescher et al., 2001; Borchers et al., 2014; Weersink et al., 1999).[8]

[8]Even though adding more control values can help control for other factors that might influence farmland values (and arguably better identify the no-till effect), it should be noted that adding more controls may also come at a cost to estimation accuracy if these controls are endogenous in and of themselves. Hence, including these variables as controls can also cause further endogeneity issues, add noise to the estimation, and also not allow for better teasing out the effect of no-till on farmland values. There is a tradeoff between including more controls versus the potential endogeneity issues these additional controls add to the estimation. Parsimony

We utilize the traditional linear panel fixed effects (FE) model to estimate equation (3). The FE model allows us to address endogeneity due to time-invariant unobservables. The county fixed effects, γ_i, control for all unobservable time-invariant determinants of agricultural land values such as unobserved topographical characteristics, unobserved soil features, and unobserved time-invariant average management abilities of farmers, which can also influence the decision to adopt no-till. In addition, the linear time trend ηt accounts for other unobserved factors affecting county-level farmland values the same way over time (i.e., technological growth, inflation), and can also help in addressing potential endogeneity issues. We also use standard errors clustered by county to account for year-to-year correlations within a county. The following are the parameters to be estimated: θ, β, η and γ. In this study, θ is the main parameter of interest and represents the impact of no-till on agricultural land values.

3.3 Robustness Checks: Alternative Specifications

To verify the stability and strength of our parameter estimates with regards to the effect of no-till on agricultural land values, we conduct several robustness checks.[9] First, we utilize an alternative specification for the no-till adoption rate variable where, instead of the percentage of acres where no-till is adopted, we use the value of total acres with no-till. For the second robustness check, we include year fixed effects in the empirical specification, rather than linear time trends. Using year fixed effects allow us to better capture the year-to-year time-varying shocks that influence all counties in the sample the same way (such as unexpected nationwide macroeconomic shocks: inflation, economic growth, population growth, etc). For the third robustness check, we combine the variable for total acres of no-till adoption with the use of year fixed effects in our empirical specification. In the fourth robustness check, we

in the empirical specification may also be compromised if we add all observable variables in the specification that can potentially influence no-till and agricultural land values.

[9]The main reason for conducting these robustness checks is to show that our main empirical findings from the linear panel FE models (in Tables 2 and 3) still largely holds even when using reasonable alternative empirical specifications or alternative estimation procedures.

add state level time trends instead of a single time trend or year fixed effects. For the fifth robustness check, we explore the effects of no-till adoption on farmland values using data only for the "I" states: Illinois, Indiana, and Iowa for census year 2007 and 2012. Finally, we use lagged no-till practice adoption rates (1 to 3 years) and the sum of no-till adoption over last 3 years in our alternative specification, as some agronomic studies argue that soil health benefits from continuous no till practice accumulates over time and immediate yield and revenue benefits are not usually observed in the first year of use (Karlen et al., 2013; Mbuthia et al., 2015).

3.4 Robustness Checks: Alternative Estimation Procedures

The robustness checks described in the previous sub-section involves testing whether our main inferences from the linear FE models hold when using alternative empirical specifications for equation (3). In the following set of robustness checks, we determine whether estimates from alternative estimation methods are still consistent with our baseline results from the traditional linear panel FE models.

First, we implement the moment-based Lewbel IV estimator (see Lewbel, 2012) to account for potential endogeneity due to correlations between time-county-varying unobservables remaining in the idiosyncratic error term and no-till adoption rates. In equation (3), we already account for endogeneity due to time-invariant unobservables. However, as alluded to in the introduction and background sections, it is possible that there may be residual endogeneity due to time and county varying unobservables that jointly influence no-till adoption and agricultural land values. For instance, time-county-varying unobservables associated with adoption of herbicide-tolerant varieties or degree of soil investments may be positively correlated with no-till adoption (NT_{it}), and these unobservables may also be positively correlated to farmland values, L_{it} (i.e., causing positive bias in our estimates). The typical approach in this case is to use instrumental variable (IV) based panel FE models (IV-FE), where the IVs are correlated with the potentially endogenous main independent variable but uncorrelated with the outcome variable (i.e., satisfying the IV exclusion restrictions). Since we do not have any external IVs that can strongly satisfy these exclusion restrictions (see footnote 2), we first utilize a Lewbel IV estimator, which do not require an external IV.

The Lewbel moment-based IV estimator utilizes heteroscedasticity in the error terms from the first-stage regressions (e.g., regression of the potentially endogenous variable NT_{it} on the observable covariates $\mathbf{X}_{it}$) to identify the coefficients of the endogenous variables in the main equation even in the absence of valid instruments. According to Lewbel (2012), the model is identified if the error terms in the first-stage equations are heteroscedastic. That is, if a subset (or all) of the exogenous control variables is correlated with the variance of the first-stage error terms but not with the covariance between the first-stage error term and the error term in the main second-stage equation, then the subset (or all) of the exogenous covariates in mean-centered form multiplied by the residuals from the first-stage equation are valid instruments.

From equation (3), the no-till variable NT_{it} is our main variable of interest that is potentially endogenous. Hence, the first-stage regression in the Lewbel (2012) approach is:

$$NT_{it} = \psi_x \mathbf{X}_{it} + u_{it}. \tag{4}$$

Lewbel (2012) has shown that $(\mathbf{X}_{it} - \bar{\mathbf{X}})\hat{u}_{it}$ can be used as a valid IV in a standard 2SLS approach if the following assumptions hold: (i) $Cov(\mathbf{X}_{it}, u_{it}^2) \neq 0$, and (ii) $Cov(\mathbf{X}_{it}, \varepsilon_{it} u_{it}) = 0$. Condition (i) above is satisfied if there is heteroscedasticity in equation (4).

We use the Breusch-Pagan (BP) test to validate the presence of heteroscedasticity in our first-stage regressions (Breusch and Pagan, 1979). The BP test rejects the null hypothesis of homoscedasticity in both the AgCensus and Iowa State data sets (i.e., BP test statistics are 117.01 (p-value < 0.01) for the AgCensus panel data and 320.31 (p-value < 0.01) for the Iowa State data). We also use the Hansen J test as an overidentification-type test for condition (ii) above (Baum and Lewbel, 2019). The Hansen J test of overidentifying restrictions indicates that our mean-centered instruments are appropriate as we fail to reject the hypothesis that the IVs are valid at the 1% level of significance (i.e., Hansen J statistics are 21.8 (p-value =

0.02) for the AgCensus panel data and 6.6 (p-value = 0.8) for the Iowa State data. Results of the tests above indicate that the Lewbel (2012) moment-based IV estimator is appropriate for our data and empirical model.

The second alternative estimation method we use is the relative correlation restrictions (RCR) approach developed by Krauth (2016). The RCR approach aims to bound the estimated causal effect of a single endogenous regressor, in the absence of IVs satisfying traditional exclusion restrictions. In our empirical context, the RCR method provides bounds on the effect of no-till on farmland values depending on an assumed range of "deviations from exogeneity". Specifically, the "deviations from exogeneity" in the RCR approach is defined based on a lambda (λ) parameter that describes (a) the unobserved correlation between the variable of interest (NT_{it}) and the error term (ε_{it}), relative to (b) the observed correlation between between the variable of interest (NT_{it}) and the control variables $\mathbf{X}_{it}$. More formally, given equation (3), we make assumptions on λ based on the following equation:

$$corr(NT_{it}, \varepsilon_{it}) = \lambda\, corr(NT_{it}, \beta X_{it} + \eta t + \gamma_i), \tag{5}$$

where $\lambda \in [\lambda_L, \lambda_H]$. If $\lambda = 0$, then this corresponds to our linear FE model (with no residual endogeneity assumed). On the other hand, if $\lambda = 1$, then the correlation between no-till and unobservables is the same as the correlation between no-till and the controls.

Krauth (2016) suggests that $[\lambda_L, \lambda_H] = [0, 1]$ is a reasonable benchmark to examine the sensitivity of the linear FE estimates. Hence, if for a reasonable range of λ between zero and λ_H the estimated bounds of the effect of no-till on farmland values are still the same sign as the linear FE model (and the bounds are statistically significant), then it requires a larger amount of residual endogeneity (i.e., true $\lambda > \lambda_H$) to invalidate our linear FE results. We can then interpret this as saying that our results are strong (and robust) since small departures from exogeneity do not change inferences from the linear FE model.[10]

[10] One can also report the minimum λ that will invalidate the results from the linear FE model (i.e., when the bounds $[\hat{\beta}_L, \hat{\beta}_H]$ includes zero). If this minimum λ is "large enough", then it implies that the linear FE results are robust.

4 Results and Discussion

4.1 Main Estimation Results

Tables 2 and 3 present estimates of the impact of no-till adoption on agricultural land values in the US Midwest based on the county-level AgCensus and Iowa state data sets, respectively. Moving from left to right in each table, we estimate the same empirical model with county fixed effects and linear time trends, while adding a progressively richer set of control variables. For example, Model 1 is our base specification where we only include the no-till adoption rate variable, the fixed effects and the time trend. In Model 2, we add weather control variables, including growing degree days, heating degree days, precipitation and precipitation squared. Next, Model 3 adds the soil quality variables (soil pH, soil organic matter and available water content) to the previous model. Lastly, the fully specified (and our preferred) model is Model 4, where we add county-level population estimates, government payment level and agricultural returns to the specification, in addition to the variables in Model 3.

We find a positive and statistically significant impact of no-till practice adoption on county-level agricultural land values. For all model specifications, an increase in the adoption rate of no-till substantially increases agricultural land values. This suggests that counties with higher no-till adoption rates also likely experience higher growth in farmland values, and this land value effect is not explained by climate, inherent soil quality features, urbanization pressures, and government payments (i.e., the control variables). Our preferred specification in Table 2 (e.g., Model 4) show that a 1% increase in the adoption rate of no-till can lead to an increase of $7.86 per acre in agricultural land values for counties in the twelve US Midwest states utilized in the census-based data. Using data from the Iowa counties, an increase in no-till adoption rates can lead to a much larger increase in the farmland values relative to the estimates from the census-based data.[11] That is, the results in Table 3 (e.g.,

[11] Please note that the larger estimated impact for Iowa counties is somewhat expected given the typically higher average agricultural land values observed in Iowa as compared to the average for all twelve states included in the other data set (See Table 1). Iowa is considered a prime agricultural production state, with high quality soils, and as such tend to have higher agricultural land values relative to other states. As such,

Model 4) suggest that a 1% increase in adoption rate for no-till can increase county-level agricultural land values by $14.75 per acre in Iowa. These estimates are robust across multiple specifications from Model 1 to Model 4, with parameter values ranging from $6.65 to $12.59 per acres for the census-based data, and from $14.75 to $24.12 for the county-level Iowa data.

Our results for the no-till adoption effect imply a high level of capitalization, showing that an increase in no-till practice adoption rate may lead to an increase in farmland values as expected future economic returns increase. This strong and positive impact of no-till on agricultural land values is consistent with relevant empirical studies that have discussed that use of soil conservation management practices (in general) positively contributing to agricultural land values (Miranowski and Hammes, 1984; Ervin and Mill, 1985; King and Sinden, 1988; Telles et al., 2016). According to these studies, investment in soil conservation practices that seek to reduce damage from soil erosion can improve and stabilize agricultural productivity, which in turn can increase farmland values. Overall the statistically significant capitalization rate results confirm the importance of including adoption of soil conservation practice in capitalization studies, and the present study provides further verification of this result by finding evidence of a positive relationship between a widely used soil conservation practice – no-till – and agricultural land values in the US. These results suggest that potential soil health improvements through no-till are likely to generate an additional benefit to landowners embodied through higher agricultural land values.

With regard to the control variables in the empirical specification, the parameter estimates from the linear FE models largely follow expectations (See Tables 2 and 3).[12] For example, the estimation results indicate that county-level population has a positive effect

it is not surprising that the marginal impact of no-till is larger using the Iowa data.

[12]Based on insights from previous literature, we initially hypothesized that the soil quality variables, population, government payments, and agricultural returns will have a positive effect on farmland values. We also hypothesized that HDD will negatively affect farmland values, while GDD will have a positive effect. However, we did not have any a priori expectations as to how precipitation will influence land values. By and large, we feel that the signs of the control variable were generally consistent with expectations (though there are some departures from what we hypothesized).

on agricultural land values. This variable capture the impact of urbanization pressure and potential development opportunities that previous studies suggest are associated with high farmland values in the US (Ifft et al., 2015). Higher productive capacity of the land (higher soil pH or larger available water content) tends to significantly increase agricultural land values in all specifications (Kik et al., 2021), while increased incidence of extreme heating degree days (higher HDD) in the cropping season leads to a decrease in farmland values.

4.2 Robustness Checks

Results of the robustness checks using alternative empirical specifications are presented in Tables 4 and 5. Detailed regression results for all the alternative empirical specifications considered in our robustness checks are in Appendix Tables A1 to A7.[13]

The results from these alternative empirical specifications are all generally consistent with the results from our main model specifications in Tables 2 and 3. The impact of no-till adoption on agricultural land values are still positive (and mostly statistically significant) for both the census-based data and the Iowa state data for all the alternative specifications examined. For example, based on the model that utilize time fixed effects rather than time trends (Column (2) in Tables 4 and 5), a 1% increase in no-till practice adoption rate at the county-level tend to increase agricultural land values by \$5.67 for the twelve US Midwest states covered by OpTIS, and by \$27.47 for the state of Iowa. However, there are results in Table 4 (e.g., the "I" state results using the AgCensus based data) where the impact of no-till are not statistically significant (but still have the expected positive sign). On the other hand, for the Iowa state data, all the robustness checks for alternative empirical specifications have statistically significant and positive no-till coefficients (Table 5). Moreover, including year fixed effects rather than linear time trends in our main empirical specification also generate similar results (Tables 4 and 5). However, the magnitude of the no-till effects on agricultural

[13]As part of the review process, a couple of referees also asked for robustness checks adding a variety of other controls to the specification (e.g., adding yield variables, crop insurance variables, etc.). Results from these additional robustness checks are seen in Appendix Tables A10-A12. In all these additional runs, our main inference remains robust.

land values becomes higher for the Iowa state data when including year fixed effects (relative to using time trends as is done in Table 3). In addition, using lagged no-till adoption rates generally still have a positive and statistically significant effect on agricultural land values (See Appendix Table A7). Though the magnitude of the effects for the lagged no-till adoption rates are relatively lower than the current year adoption percentage specification in the main model.

The robustness check results for the two alternative estimation procedures we used — the Lewbel moment-based IV estimator and the RCR approach — are presented in Tables 6 and 7, respectively. For the Lewbel model, we still find that no-till adoption percentage has a positive effect on agricultural land values (Table 6). However, the AgCensus results are not statistically significant (though still positive). In contrast, the no-till effect is positive and strongly significant for the Lewbel runs using the Iowa state data. The magnitudes of the no-till effects also tend to be higher than our results from the linear FE model.

With regards to the RCR estimation strategy, we present the estimated bounds of the no-till effects using our base specification without control variables (Model 1) and the fully specified model with all controls (Model 4).[14] In the top panel of Table 7, using the base specification, the RCR analysis suggest that the linear FE results are robust to even moderate or large departures from exogeneity.[15] If the correlation between no-till and the unobservables is no larger than correlation between no-till and the observables in the base specification (i.e., $\lambda = 1$), then the RCR bounds of the estimated no-till effects in both the AgCensus and Iowa state data are still positive with fairly narrow bounds. It would take a lambda correlation of at least 157% for the RCR bounds to include zero in the AgCensus runs and 178% for the Iowa state runs.

In the lower panel of Table 7, RCR results using the fully specified model (with all controls) implies that if the correlation between no-till and the unobservables are about less

[14]The RCR results for Model 2 (with weather variables as additional controls) and Model 3 (with weather and soil quality variables as additional controls), are presented in Appendix Tables A8 and A9.

[15]Krauth (2016) indicates that moderate departures from exogeneity is when the lambda parameter is around 0.5, and large departures is when it is around 1.0 or larger.

than half ($\lambda = 0.5$) of the correlation between no-till and the control variables included in Model 4, then the RCR bounds do not include zero and are still positive and significant in most cases (especially for the Iowa state data). This suggests that our linear FE results for the fully specified model are robust to only mild and moderate departures from exogeneity. Nonethelesss, as noted in footnote 8, it could also be that if these additional control variables are endogenous in and of themselves, then it is possible that these variables are adding more residual endogeneity issues. This is consistent with the tradeoffs seen when adding potentially endogenous control variables that can help account for unobservables correlated with the main variable of interest and the error term, but can also cause their own endogeneity issues in the estimation. The minimum lambda correlations that would result in zero being included in the RCR bounds are 44% for the AgCEnsus data and 98% for the Iowa state data. The range of the bounds of the no-till results are also fairly narrow for lambdas below 0.5 (even though some of them are statistically insignificant). On balance, the RCR model results for the fully specified model are still supportive of the linear FE results that higher no-till adoption generally increases farmland values, though only under mild to moderate departures from the strict exogeneity assumption.

5 Conclusions

Agricultural land is an important economic asset for most farmers, and the value of agricultural land are determined by the productive capacity of the soil and the expected economic returns to agricultural production, among many other factors (Borchers et al., 2014). Thus, adoption of soil conservation management practices that improves soil health and reduces soil erosion is usually viewed as potentially contributing to higher farmland values (Boyle, 2006; Kik et al., 2021). However, empirical evidence on the relationship between soil conservation practices (such as no-till) and farmland values has been limited. The main objective of this study is to investigate the impact of no-till practice adoption on agricultural land values in the US Midwest. Two unique county-level farmland value data sets – one based on the census of agriculture and one from Iowa farmland surveys – are separately merged with a novel satellite-based no-till adoption data set to fulfill the study objective. The county-level census-based data encompasses twelve states in the US Midwest for the census years 2007, 2012 and 2017, while the Iowa data covers 99 counties in the state for the years from 2005 to 2016. Linear fixed effects models, as well as external-IV-free estimation strategies, are estimated for a variety of empirical specifications to explore the effects of no-till adoption on farmland values.

The results show a positive and statistically significant effect of no-till adoption on US agricultural land values. For almost all model specifications in our analysis, an increase in no-till adoption leads to a substantial increase in agricultural land values. For example, based on the census-based farmland value data for twelve US Midwest states, a 1% increase in the use no-till practice in the county increase farmland value by $7.86 per acre (using our preferred model that includes all control variables). On the other hand, our estimates based on the Iowa county data suggest that a 1% increase in no-till adoption rates increases county-level agricultural land values by $14.75 per acre (for our preferred model that includes all control variables). A number of robustness checks also support these findings. Hence, results from this study provide empirical evidence that private economic and environmental benefits from no-till adoption are likely capitalized into farmland values.

Findings from the present study point to a couple of important implications. First, our results provide support to the notion that productivity effects of adopting soil conservation management practices (like no-till) are capitalized into farmland values. Hence, demonstrating this farmland value capitalization effect and effectively communicating this "benefit" to farmland owners can help further encourage adoption of this environmentally friendly practice. The farmland value capitalization effect of no-till can be viewed as an additional benefit that can help further incentivize uptake of this practice (especially farmers who own the land they operate). Notwithstanding this land value benefit of no-till, we believe that payments from federal cost-share programs such as the Environmental Quality Incentives Program (EQIP) would still have a role to play in terms of better aligning private incentives to adopt no-till with the off-site public environmental benefits from the soil health practice. There is still a classic positive externality issue here even when recognizing the farmland value increasing effect of no-till, which can then result in "underprovision" of off-site societal benefits. This potential market failure suggests that public policy interventions (like EQIP) can help internalize the external societal benefits of no-till for more optimal provision of its environmental benefits (Rejesus et al., 2021).[16] Second, as already alluded to above, communicating and informing farmland owners of the agricultural land value benefits of no-till adoption is critical for further promotion of this practice in US row crop agriculture. Cooperative extension specialists with responsibilities related to soil health management and conservation should include the potential farmland value enhancement from adopting no-till when providing extension materials about the benefits of this practice to their farmer clientele. Lack of information about the various short-term and long-term benefits of no-till has been viewed as a potential barrier to adoption because, in this case, one cannot fully assess if the private costs of investment in this practice is commensurate with the private benefits one is expected to receive (Gardner and Barrows, 1985; Rodriguez et al., 2009)

Even though the present study provides important insights regarding the impact of no-till practice adoption on agricultural land values, it is important to acknowledge the limitations of the study and discuss potentially fruitful avenues for future research. First, our study only explores the relationship between agricultural land values and one single soil conservation practice – no-till. To provide a better understanding on the effects of soil health and soil conservation technology adoption on agricultural land values, it may be necessary to capture the simultaneous impacts of a number of other agricultural conservation practices (i.e., cover

[16] Farmers typically bear all the costs of no-till adoption when there are no cost-share payments or subsidies available. Hence, from a neoclassical economic perspective, farmers would invest in no-till to the point where marginal private benefits (including land value capitalization) equal private marginal costs. However, if there are additional off-site environmental benefits from no-till adoption that society values (e.g., carbon sequestration, reduced runoff to rivers), then there is still a "mismatch" on who receives benefits and who bears the costs. In this case, there is a role for public policy interventions like EQIP.

crops, nutrient management practices, off-field structural practices, etc.) on farmland values. Second, the geographical scope of the current study is limited to the US Midwest. Thus, our study does not cover other regions in the US with relatively higher no-till adoption rates (e.g., the Northeastern and the Mid-Atlantic US states). To have better external validity, it may be useful to investigate the impact of no-till practice on farmland values for other regions in the US (or other countries with higher no-till adoption rates).

Third, for particular regions with widely differing land quality characteristics, adoption of no-till practice may have different effects on farmland values, having data for more land characteristics would also allow one to more accurately estimate the impact of higher no-till practice adoption rates on agricultural land values for a specific area. Fourth, our analysis was conducted at the county-level, which is a more aggregate level compared to using farm-level or plot-level data. Although an analysis at the county-level provides important inferences with regards to the aggregate impact of no-till to farmland values, future assessments using farm- or plot-level data may provide additional nuance, especially if one can separate out the impacts of continuous no-till adoption (i.e., sustained yearly adoption of no-till over time) versus non-continuous no-till adoption (e.g., rotational or alternating no-till adoption). Lastly, our empirical analysis dealt with the issue of endogeneity due to time-county-varying unobservables by utilizing two recently developed external-IV-free models of Lewbel (2012) and Krauth (2016). These methods were chosen because we were not able to find strong external IVs that would allow us to implement more traditional panel IV approaches to deal with this kind of endogeneity (e.g., 2SLS, control function approaches). Hence, if valid external instruments are available, it would be useful to evaluate whether our inferences would still hold when using these traditional panel IV methods. We leave all these potential extensions for future work.

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Table 1: Description and Summary Statistics of Variables

Variable	Description	Mean	SD	Min	Max
Agland value	Agricultural land values in census data ($/acre)	4525.359	2039.682	701	20635
Iowa agland value	Agricultural land values in Iowa ($ /acre)	5862.936	2460.035	1321	12861.700
No-till percentage	Percentage of acres with no-till in census data (%)	27.548	12.552	0	79.400
Iowa no-till percentage	Percentage of acres with no-till in Iowa (%)	26.796	12.132	0	81
GDD	Growing degree days ($8 - 29$°C)	1955.566	256.374	1127.851	2750.691
HDD	Heating degree days (above 29°C)	2.546	7.751	0	128.923
prep	Precipitation (growing season average, 1000mm)	527.671	141.153	103.756	1161.698
prep_s	Precipitation squared	298359.5	162703.4	10765.33	1349542
ph30	Soil pH	6.138	.342	5.273	7.299
om30	Soil oganic matter (%)	3.355	1.553	1.231	12.601
awc30	Available water content (m^3/m^3)	0.195	0.011	0.140	0.220
pop	County-level population	75881.98	254953.5	797	5285107
return	Agricultural returns ('000 $)	59183.68	53513.68	-25728	405893
government payment	Federal gov't payments ('000 $)	5171.374	3262.029	34	22843

Table 2: Impact of no-till adoption rate (%) on agricultural land values (AgCensus)

	Model 1	Model 2	Model 3	Model 4
No-till pct	11.7231***	6.6488**	12.5861***	7.8585***
	(2.5147)	(2.3646)	(2.7172)	(2.2682)
Time Trend	262.3628***	282.3480***	377.2659***	229.0450***
	(5.1196)	(9.3391)	(12.8048)	(14.2899)
GDD		0.7855	-6.3098***	-3.7918***
		(0.4557)	(0.9337)	(0.7526)
HDD		2.7307	-36.6118***	-11.8008***
		(1.8155)	(3.2994)	(2.9563)
Precipitation		-7.2395***	-4.5129***	-3.4353***
		(0.9583)	(0.9584)	(0.8260)
Precipitation squared		0.0067***	0.0027**	0.0026**
		(0.0010)	(0.0009)	(0.0008)
Soil pH			6367.4898***	4386.5631***
			(1352.6904)	(911.1899)
Soil Organic Matter			-87.9991	79.9170
			(457.2162)	(383.7317)
Available Water Content			1.091e+05**	59058.6416*
			(33753.1594)	(22960.3608)
Population				0.0091***
				(0.0021)
Government Payment				-0.0583
				(0.0423)
Agricultural Returns				0.0155***
				(0.0010)
County FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.732	0.751	0.790	0.862
Observations	1938	1938	1291	1291

Note: The dependent variable is the agricultural land values of 12 states covered by OpTIS project for census year 2007, 2012 and 2017. Each specification includes county fixed effects. The Standard errors are clustered by county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Impact of no-till adoption rate (%) on agricultural land values (Iowa state)

	Model 1	Model 2	Model 3	Model 4
No-till pct	24.1200***	20.4802***	18.0743***	14.7493***
	(3.9758)	(3.2777)	(3.2201)	(2.8021)
Time Trend	517.2693***	535.5070***	560.0809***	494.4271***
	(10.8091)	(11.8274)	(9.6483)	(10.6160)
GDD		0.6045*	0.6053*	0.9412***
		(0.2474)	(0.2467)	(0.2083)
HDD		-16.5870*	-7.4506	-17.7052*
		(6.3712)	(6.1129)	(7.0361)
Precipitation		-8.8096***	-8.9029***	-5.2328***
		(0.8072)	(0.7972)	(0.9011)
Precipitation squared		0.0049***	0.0049***	0.0024***
		(0.0006)	(0.0006)	(0.0007)
Soil pH			12755.9973**	9453.5593**
			(3950.1878)	(3450.0006)
Soil Organic Matter			716.7424	-1266.0807
			(1153.0621)	(1371.7797)
Available Water Content			2.611e+05***	2.396e+05***
			(59737.0435)	(61063.8504)
Population				0.0186
				(0.0110)
Government Payment				-0.0170**
				(0.0058)
Agricultural Returns				0.0119***
				(0.0012)
County FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.767	0.822	0.830	0.858
Observations	1188	1188	1188	1188

Note: The dependent variable is the agricultural land values of 99 counties in Iowa state for years 2005-2016. Each specification includes county fixed effects. Standard errors are clustered by county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Robustness Checks: Effects of No-Till Practice on Land Values (AgCensus)

	(1)	(2)	(3)	(4)	(5)
No-till acre	0.0036**		0.0031*		
	(0.0011)		(0.0014)		
No-till pct		5.6712*		5.8664**	4.7494
		(2.6419)		(1.9811)	(3.7244)
GDD	-3.8976***	-2.7708**	-2.8269**	2.5141**	0.2406
	(0.7489)	(0.9467)	(0.9365)	(0.8892)	(1.4979)
HDD	-11.1644***	21.5648***	21.8982***	-15.6245**	-8.4667
	(2.9469)	(3.2917)	(3.2698)	(5.2422)	(7.9632)
Precipitation	-3.4451***	-5.8475***	-5.7822***	-1.3030	-0.8491
	(0.8272)	(1.0399)	(1.0407)	(0.8703)	(2.1902)
Precipitation squared	0.0025**	0.0046***	0.0045***	0.0017*	-0.0005
	(0.0008)	(0.0010)	(0.0010)	(0.0008)	(0.0023)
Soil pH	4148.4820***	1984.1514*	1791.1990*	4166.2398***	7911.7077**
	(893.2739)	(931.6872)	(904.6500)	(1082.3989)	(2424.4967)
Soil Organic Matter	105.4674	29.4002	45.9756	28.5854	-170.9890
	(381.6893)	(390.5869)	(391.0231)	(361.5701)	(686.8492)
Available Water Content	58952.2255**	-1.423e+04	-1.401e+04	70674.1565**	1.420e+05***
	(22638.2040)	(20989.0640)	(21023.2504)	(27043.7653)	(39266.7964)
Population	0.0085***	0.0134*	0.0130	0.0072**	0.0162
	(0.0022)	(0.0068)	(0.0068)	(0.0026)	(0.0102)
Government Payment	-0.0581	0.0291	0.0291	-0.0478	-0.0768
	(0.0418)	(0.0485)	(0.0479)	(0.0307)	(0.0452)
Agricultural Returns	0.0152***	0.0256***	0.0252***	0.0108***	0.0137***
	(0.0010)	(0.0011)	(0.0011)	(0.0010)	(0.0014)
Time Trend	227.8859***			401.2259***	309.3881***
	(14.2970)			(30.6852)	(28.5231)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	No
State × Year Time Trend	No	No	No	Yes	No
Adjusted R^2	0.862	0.791	0.792	0.905	0.922
Observations	1291	1291	1291	1291	586

Note: (1) The table shows the combined results of the robustness checks for the AgCensus data using alternative specifications. (2) The dependent variable is the agricultural land values of states covered by OpTIS project for census year 2007 and 2012. (3) The first column indicates the result for the first robustness check (using adoption acres of no-till practice). The second column shows the result for the second robustness check (using year fixed effects instead of time trends). The third column indicates the result for the third robustness check (using no-till adoption acres with year fixed effects). The fourth column indicates the result for the third robustness check (using state-level year fixed effects). The fifth column presents the result for the last robustness check (using the agricultural land values and no-till adoption rates only for the "I" states: Illinois, Indiana, and Iowa). (4) Standard errors are clustered by county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Robustness Checks: Effects of No-Till Practice on Land Values (Iowa state)

	(1)	(2)	(3)
No-till acre	0.0055***		0.0114***
	(0.0013)		(0.0028)
No-till pct		27.4698***	
		(7.1197)	
GDD	0.9110***	1.4334**	1.4060**
	(0.2065)	(0.4268)	(0.4229)
HDD	-14.8359*	-69.0825***	-64.3161***
	(6.6781)	(13.8702)	(12.9007)
Precipitation	-5.1561***	0.6727	0.8291
	(0.9023)	(1.6111)	(1.6343)
Precipitation squared	0.0023***	-0.0008	-0.0009
	(0.0007)	(0.0012)	(0.0013)
Soil pH	9348.0501**	6070.8147	5559.2168
	(3314.6692)	(5302.5667)	(5277.0166)
Soil Organic Matter	-1206.5415	-1.832e+04***	-1.813e+04***
	(1342.2317)	(2427.3915)	(2390.7923)
Available Water Content	2.390e+05***	-1.324e+05	-1.341e+05
	(59703.3685)	(1.008e+05)	(99350.5273)
Population	0.0186	0.0945**	0.0947**
	(0.0109)	(0.0280)	(0.0280)
Government Payment	-0.0169**	-0.0596*	-0.0595*
	(0.0058)	(0.0268)	(0.0267)
Agricultural Return	0.0118***	0.0310***	0.0306***
	(0.0012)	(0.0036)	(0.0036)
Time Trend	493.8192***		
	(10.7095)		
County FE	Yes	Yes	Yes
Year FE	No	Yes	Yes
Adjusted R^2	0.857	0.474	0.475
Observations	1188	1188	1188

Note: (1) The table shows the combined results of the robustness checks for the Iowa data using alternative specifications. (2) The dependent variable is the agricultural land values of 99 counties in Iowa state for years 2005-2016. (3) The first column indicates the result for the first robustness check (the main specification includes adoption acres of no-till, weather variables, soil fertility variables, and county-level population level as controls. The second column shows the result for the second robustness check (using year fixed effects instead of time trends). The third column indicates the result for the third robustness check (using no-till adoption acres with year fixed effects). (4) Standard errors are clustered by county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Robustness Check: Lewbel IV estimation strategy

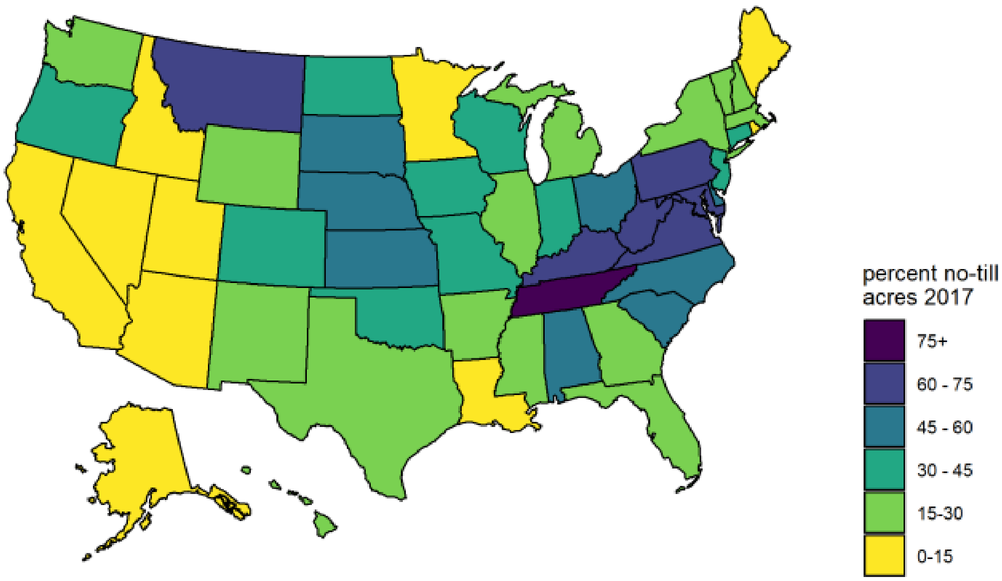
	AgCensus	Iowa state
Dependent variable:	Agricultural land value	Agricultural land value
No-till pct	25.1644	36.8947***
	(27.5031)	(10.9638)
GDD	-3.1818***	1.2120***
	(1.2284)	(0.2591)
HDD	-13.6510***	-27.7064***
	(4.2797)	(10.3487)
Precipitation	-2.3629	-5.0694***
	(1.9664)	(0.9777)
Precipitation squared	0.0018	0.0023***
	(0.0016)	(0.0008)
Soil pH	4459.0195***	7204.5686**
	(1107.6704)	(3447.5441)
Soil Organic Matter	-9.1238	-1294.1670
	(414.4108)	(1340.9412)
Available Water Content	60577.6792**	2.252e+05***
	(24141.8753)	(58825.9208)
Population	0.0106***	0.0210*
	(0.0033)	(0.0122)
Government Payment	-0.0573	-0.0180***
	(0.0413)	(0.0061)
Agricultural Returns	0.0146***	0.0110***
	(0.0016)	(0.0013)
Time Trend	234.1912***	488.7098***
	(16.1167)	(10.5087)
County FE	Yes	Yes
Adjusted R^2	0.696	0.836
Observations	1291	1188

Note: (1) The table shows the results of the Lewbel IV robustness checks for both the AgCensus and Iowa state data sets.(2) Standard errors are clustered by county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

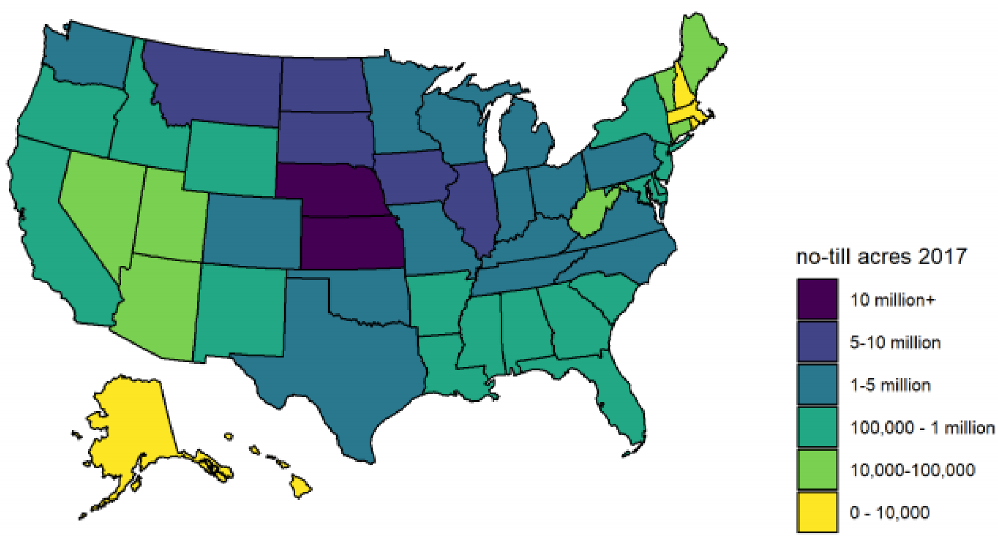
Table 7: Robustness Check: Relative Correlation Restriction (RCR) estimation strategy

	AgCensus	Iowa state
Dependent variable:	Agricultural land value	Agricultural land value
Base specification (Model 1):		
Linear FE model estimate	11.7231***	24.1200***
(95% CI)	(6.8211, 16.6251)	(17.0958, 31.1443))
Bounds, $0 \leq \lambda \leq 0.1$	[10.9827, 11.7231]***	[22.7963, 24.1200]***
(95%CI)	(6.9872, 15.7072)	(15.8878, 30.9869)
Bounds, $0 \leq \lambda \leq 0.2$	[10.2421, 11.7231]***	[21.4721, 24.1200]***
(95%CI)	(6.1969, 15.7072)	(14.4597, 30.9869)
Bounds, $0 \leq \lambda \leq 0.3$	[9.5013, 11.7231]***	[20.1469, 24.1200]***
(95%CI)	(5.3691, 15.7072)	(12.9706, 30.9869)
Bounds, $0 \leq \lambda \leq 0.4$	[8.7600, 11.7231]***	[18.8202, 24.1200]***
(95%CI)	(4.5059, 15.7072)	(11.4233, 30.9869)
Bounds, $0 \leq \lambda \leq 0.5$	[8.0181, 11.7231]***	[17.4915, 24.1200]***
(95% CI)	(3.6096, 15.7072)	(9.8212, 30.9869)
Bounds, $0 \leq \lambda \leq 1$	[4.2940, 11.7231]	[10.7999. 24.1200]**
(95%CI)	(-1.2725, 15.7072)	(1.1162, 30.9869)
Minimum λ for which bounds include zero	1.5700	1.7853
Model with all controls (Model 4):		
Linear FE model estimate	7.8585***	14.7493***
(95% CI)	(3.4061, 12.3108)	(9.0719, 20.4266)
Bounds, $0 \leq \lambda \leq 0.1$	[6.1065, 7.8585]	[13.2989, 14.7493]***
(95%CI)	(-17.2196, 30.6011)	(7.3884, 20.6188)
Bounds, $0 \leq \lambda \leq 0.2$	[4.3402, 7.8585]	[11.8407, 14.7493]***
(95%CI)	(-20.4585, 30.6011)	(5.5258, 20.6188)
Bounds, $0 \leq \lambda \leq 0.3$	[2.5545, 7.8585]	[10.3737, 14.7493]***
(95%CI)	(-22.3393, 30.6011)	(3.9919, 20.6188)
Bounds, $0 \leq \lambda \leq 0.4$	[0.7436, 7.8585]	[8.8966, 14.7493]
(95%CI)	(-26.2185, 30.6011)	(-0.42077, 20.6188)
Bounds, $0 \leq \lambda \leq 0.5$	[-1.0984, 7.8585]	[7.4084, 14.7493]
(95% CI)	(-28.7005, 30.6011)	(-2.1159, 20.6188)
Bounds, $0 \leq \lambda \leq 1$	[-11.0399, 7.8585]	[-0.2468, 14.7493]
(95%CI)	(-42.6923, 30.6011)	(-12.6221, 20.6188)
Minimum λ for which bounds include zero	0.4406	0.9843

Note: Linear FE model estimates and RCR bounds for the effect of no-till on agricultural land values using AgCensus and Iowa state datasets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$



(a) Map of no-till percentages in each state for 2017



(b) Map of no-till acres in each state for 2017

Figure 1: Map of No-Till Adoption in Each State in the US for 2017 (Source: The 2017 U.S. Census of Agriculture)

Appendix

Table A1: Robustness Check: Impact of no-till acres on farmland values (AgCensus)

	Model 1	Model 2	Model 3	Model 4
No-till acre	0.0084***	0.0058***	0.0076***	0.0036**
	(0.0010)	(0.0010)	(0.0012)	(0.0011)
Time Trend	260.9311***	277.8934***	368.1288***	227.8859***
	(5.1706)	(9.2357)	(12.9765)	(14.2970)
GDD		0.6033	-6.2478***	-3.8976***
		(0.4486)	(0.9149)	(0.7489)
HDD		3.4547	-34.4182***	-11.1644***
		(1.7655)	(3.3101)	(2.9469)
Precipitation		-6.9049***	-4.2228***	-3.4451***
		(0.9349)	(0.9295)	(0.8272)
Precipitation squared		0.0064***	0.0024**	0.0025**
		(0.0009)	(0.0009)	(0.0008)
Soil pH			5776.1304***	4148.4820***
			(1334.0289)	(893.2739)
Soil Organic Matter			-45.2698	105.4674
			(448.1153)	(381.6893)
Available Water Content			1.065e+05**	58952.2255**
			(32286.2543)	(22638.2040)
Population				0.0085***
				(0.0022)
Government Payment				-0.0581
				(0.0418)
Agricultural Returns				0.0152***
				(0.0010)
County FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.738	0.754	0.795	0.862
Observations	1938	1938	1291	1291

Note: The table shows the results of the first robustness check. The dependent variable is the agricultural land values of 12 states covered by OpTIS project for census year 2007, 2012 and 2017. Each specification includes county fixed effects. Standard errors are clustered by county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2: Robustness Check: Impact of no-till acres on farmland values (Iowa State)

	Model 1	Model 2	Model 3	Model 4
No-till acre	0.0100***	0.0081***	0.0071***	0.0055***
	(0.0018)	(0.0015)	(0.0015)	(0.0013)
Time Trend	514.5190***	533.4924***	558.3855***	493.8192***
	(10.9929)	(12.0487)	(9.8206)	(10.7095)
GDD		0.5771*	0.5807*	0.9110***
		(0.2469)	(0.2468)	(0.2065)
HDD		-12.9795*	-4.3149	-14.8359*
		(5.8105)	(5.7727)	(6.6781)
Precipitation		-8.6324***	-8.7481***	-5.1561***
		(0.8217)	(0.8100)	(0.9023)
Precipitation squared		0.0048***	0.0048***	0.0023***
		(0.0006)	(0.0006)	(0.0007)
Soil pH			12461.7713**	9348.0501**
			(3730.9433)	(3314.6692)
Soil Organic Matter			780.8172	-1206.5415
			(1118.2425)	(1342.2317)
Available Water Content			2.593e+05***	2.390e+05***
			(58214.8943)	(59703.3685)
Population				0.0186
				(0.0109)
Government Payment				-0.0169**
				(0.0058)
Agricultural Returns				0.0118***
				(0.0012)
County FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.769	0.822	0.830	0.857
Observations	1188	1188	1188	1188

Note: The table shows the results of the first robustness check. The dependent variable is the agricultural land values of 99 counties in Iowa state for years 2005-2016. Each specification includes county fixed effects. Standard errors are clustered by county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: Robustness Check: Impact of no-till adoption (%) on farmland values (AgCensus)

	Model 1	Model 2	Model 3	Model 4
No-till pct	23.7654***	5.7694	15.4465***	5.6712*
	(4.6456)	(3.0555)	(4.1191)	(2.6419)
GDD		-12.5154***	-8.8192***	-2.7708**
		(0.2826)	(1.5710)	(0.9467)
HDD		28.3037***	12.4600**	21.5648***
		(2.7385)	(4.8118)	(3.2917)
Precipitation		-14.6578***	-13.7783***	-5.8475***
		(1.0927)	(1.3913)	(1.0399)
Precipitation squared		0.0100***	0.0085***	0.0046***
		(0.0011)	(0.0014)	(0.0010)
Soil pH			2565.5959	1984.1514*
			(1548.9380)	(931.6872)
Soil Organic Matter			-739.6530	29.4002
			(516.4435)	(390.5869)
Available Water Content			-3.315e+04	-1.423e+04
			(37745.8027)	(20989.0640)
Population				0.0134*
				(0.0068)
Government Payment				0.0291
				(0.0485)
Agricultural Returns				0.0256***
				(0.0011)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.018	0.613	0.436	0.791
Observations	1938	1938	1291	1291

Note: The table shows the results of the second robustness check. The dependent variable is the agricultural land values of 12 states covered by OpTIS project for census year 2007, 2012 and 2017. Each specification includes county fixed effects and year fixed effects. Standard errors are clustered by county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A4: Robustness Check: Impact of no-till adoption (%) on farmland values (Iowa state)

	Model 1	Model 2	Model 3	Model 4
No-till pct	47.4402***	46.0387***	44.7571***	27.4698***
	(10.1450)	(10.1277)	(9.1006)	(7.1197)
GDD		0.1836	0.2263	1.4334**
		(0.3352)	(0.3108)	(0.4268)
HDD		-37.9164*	-55.4063***	-69.0825***
		(14.9579)	(14.2610)	(13.8702)
Precipitation		-9.8763***	-9.0754***	0.6727
		(1.8155)	(1.7819)	(1.6111)
Precipitation squared		0.0070***	0.0063***	-0.0008
		(0.0015)	(0.0014)	(0.0012)
Soil pH			15260.6900*	6070.8147
			(6657.9187)	(5302.5667)
Soil Organic Matter			-1.883e+04***	-1.832e+04***
			(2420.6342)	(2427.3915)
Available Water Content			-2.477e+05*	-1.324e+05
			(1.042e+05)	(1.008e+05)
Population				0.0945**
				(0.0280)
Government Payment				-0.0596*
				(0.0268)
Agricultural Returns				0.0310***
				(0.0036)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.037	0.056	0.171	0.474
Observations	1188	1188	1188	1188

Note: The table shows the results of the second robustness check. The dependent variable is the agricultural land values of 99 counties in Iowa state for years 2005-2016. Each specification includes county fixed effects and year fixed effects. Standard errors are clustered by county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5: Robustness Check: Impact of no-till acres on farmland values (AgCensus)

	Model 1	Model 2	Model 3	Model 4
No-till acre	0.0152***	0.0082***	0.0136***	0.0031*
	(0.0020)	(0.0014)	(0.0019)	(0.0014)
GDD		-12.4447***	-8.2750***	-2.8269**
		(0.2840)	(1.5315)	(0.9365)
HDD		28.4025***	13.9450**	21.8982***
		(2.6705)	(4.7436)	(3.2698)
Precipitation		-13.8660***	-12.3296***	-5.7822***
		(1.0687)	(1.3249)	(1.0407)
Precipitation squared		0.0094***	0.0073***	0.0045***
		(0.0011)	(0.0013)	(0.0010)
Soil pH			1688.5182	1791.1990*
			(1473.7436)	(904.6500)
Soil Organic Matter			-668.8424	45.9756
			(509.1265)	(391.0231)
Available Water Content			-3.091e+04	-1.401e+04
			(36389.4679)	(21023.2504)
Population				0.0130
				(0.0068)
Government Payment				0.0291
				(0.0479)
Agricultural Returns				0.0252***
				(0.0011)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.034	0.621	0.466	0.792
Observations	1938	1938	1291	1291

Note: The table shows the results of the third robustness check. The dependent variable is the agricultural land values of 12 states covered by OpTIS project for census year 2007, 2012 and 2017. Each specification includes county fixed effects and year fixed effects. Standard errors are clustered by county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6: Robustness Check: Impact of no-till acres on farmland values (Iowa state)

	Model 1	Model 2	Model 3	Model 4
No-till acre	0.0217***	0.0208***	0.0196***	0.0114***
	(0.0038)	(0.0038)	(0.0036)	(0.0028)
GDD		0.2083	0.2269	1.4060**
		(0.3386)	(0.3099)	(0.4229)
HDD		-31.3475*	-48.7100***	-64.3161***
		(12.9683)	(12.5603)	(12.9007)
Precipitation		-9.2728***	-8.5506***	0.8291
		(1.8849)	(1.8412)	(1.6343)
Precipitation squared		0.0066***	0.0059***	-0.0009
		(0.0015)	(0.0015)	(0.0013)
Soil pH			13810.0788*	5559.2168
			(6344.0176)	(5277.0166)
Soil Organic Matter			-1.843e+04***	-1.813e+04***
			(2412.1360)	(2390.7923)
Available Water Content			-2.507e+05*	-1.341e+05
			(1.048e+05)	(99350.5273)
Population				0.0947**
				(0.0280)
Government Payment				-0.0595*
				(0.0267)
Agricultural Returns				0.0306***
				(0.0036)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.053	0.070	0.181	0.475
Observations	1188	1188	1188	1188

Note: The table shows the results of the third robustness check. The dependent variable is the agricultural land values of 99 counties in Iowa state for years 2005-2016. Each specification includes county fixed effects and year fixed effects. Standard errors are clustered by county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A7: Robustness Check: Impact of (lagged) no-till adoption on agricultural land values

	AgCensus				Iowa state			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No-till pct$_{it-1}$	8.3226***				6.3337**			
	(2.1381)				(2.3683)			
No-till pct$_{it-2}$		3.6289				12.3871**		
		(2.4421)				(4.1450)		
No-till pct$_{it-3}$			5.6506*				0.9286	
			(2.3868)				(4.1925)	
No-till pct (3 years)				4.7852***				6.4374*
				(1.0721)				(3.1077)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.626	0.638	0.572	0.605	0.810	0.693	0.714	0.697
Observations	1292	1292	1292	1292	1089	990	891	891

Note: (1) The table shows the combined results of the last robustness checks. (2) For column (1) to (4), the dependent variable is the agricultural land values of states covered by OpTIS project for census year 2007 and 2012. (3) For column (5) to (8), the dependent variable is the agricultural land values of 99 counties in Iowa state for years 2005-2016. (3) Column (1) and (5) indicate the results for 1-year lagged no-till adoption rates. Column (2) and (6) show the results for 2-year lagged no-till adoption rates. Column (3) and (7) present the results for 3-year lagged non-till adoption rates. Column (4) and (8) indicate the results for the sum of no-till adoption rates over last 3 years (from $t-1$ to $t-3$). (4) Standard errors are clustered by county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A8: Robustness Check: Relative Correlation Restriction (RCR) estimation strategy (AgCensus)

	Model 2	Model 3
Dependent variable:	Agricultural land value	Agricultural land value
Linear FE model estimate	6.6488***	12.5861***
(95% CI)	(1.7569, 11.5407)	(7.1439, 18.0282)
Bounds, $0 \leq \lambda \leq 0.1$	[5.5777, 6.6488]***	[10.6234, 12.5861]***
(95%CI)	(1.7469, 10.4518)	(6.0147, 17.1241)
Bounds, $0 \leq \lambda \leq 0.2$	[4.4981, 6.6488]**	[8.6441, 12.5861]***
(95%CI)	(0.5927, 10.4518)	(3.7365, 17.1241)
Bounds, $0 \leq \lambda \leq 0.3$	[3.4096, 6.6488]	[6.6431, 12.5861]**
(95%CI)	(-0.6161, 10.4518)	(1.5099, 17.1241)
Bounds, $0 \leq \lambda \leq 0.4$	[2.3114, 6.6488]	[4.6155, 12.5861]
(95%CI)	(-1.8780, 10.4518)	(-0.8524, 17.1241)
Bounds, $0 \leq \lambda \leq 0.5$	[1.2031, 6.6488]	[2.5554, 12.5861]
(95% CI)	(-3.1906, 10.4518)	(-2.8713, 17.1241)
Bounds, $0 \leq \lambda \leq 1$	[-4.5161, 6.6488]	[-8.4745, 12.5861]
(95%CI)	(-10.4310, 10.4518)	(-16.4580, 17.1241)
(95% CI)	(-52.5323, 10.4518)	$(-\infty, \infty)$
Minimum λ for which bounds include zero	0.6074	0.6214

Note: Linear FE model estimates and RCR bounds for the effect of no-till on agricultural land values using AgCensus dataset based on the model specification Model 2 and Model 3. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A9: Robustness Check: Relative Correlation Restriction (RCR) estimation strategy (Iowa state)

	Model 2	Model 3
Dependent variable:	Agricultural land value	Agricultural land value
Linear FE model estimate	20.4802***	18.0743***
(95% CI)	(14.2309, 26.7295)	(11.9109, 24.2377)
Bounds, $0 \leq \lambda \leq 0.1$	[19.1478, 20.4802]***	[16.6399, 18.0743]***
(95%CI)	(13.3613, 26.2196)	(9.6486, 24.9814)
Bounds, $0 \leq \lambda \leq 0.2$	[17.8108, 20.4802]***	[15.1983, 18.0743]***
(95%CI)	(11.9147, 26.2196)	(8.0535, 24.9814)
Bounds, $0 \leq \lambda \leq 0.3$	[16.4686, 20.4802]***	[13.7488, 18.0743]***
(95%CI)	(10.4028, 26.2196)	(6.4181, 24.9814)
Bounds, $0 \leq \lambda \leq 0.4$	[15.1206, 20.4802]***	[12.2904, 18.0743]***
(95%CI)	(8.8283, 26.2196)	(4.7268, 24.9814)
Bounds, $0 \leq \lambda \leq 0.5$	[13.7659, 6.20.4802]***	[10.8220, 18.0743]***
(95% CI)	(7.1948, 26.2196)	(3.0520, 24.9814)
Bounds, $0 \leq \lambda \leq 1$	[6.8669, 20.4802]	[3.2950, 18.0743]
(95%CI)	(-1.7406, 26.2196)	(-6.3109, 24.9814)
Minimum λ for which bounds include zero	1.4782	1.2111

Note: Linear FE model estimates and RCR bounds for the effect of no-till on agricultural land values using Iowa state dataset based on the model specification Model 2 and Model 3. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A10: Robustness Check: Estimates of the Effects of No-Till Practice on Land Values

	AgCensus		Iowa state	
	(1)	(2)	(3)	(4)
No-till pct	11.6006***	10.6542***	11.8805***	11.3713***
	(2.9362)	(2.8416)	(2.9870)	(2.7965)
Time Trend	378.1155***	394.1629***	576.9026***	571.1807***
	(15.7352)	(12.8013)	(12.7672)	(13.6543)
GDD	-5.9973***	-7.2962***	0.6230**	1.9118***
	(1.0037)	(0.9651)	(0.2244)	(0.2648)
HDD	-41.6546***	-41.1254***	-74.9529***	-38.3320***
	(4.6736)	(3.2983)	(10.1800)	(7.4201)
Precipitation	-3.6757**	-3.8315***	-0.7209	-3.4316***
	(1.1223)	(1.0491)	(0.6601)	(0.7089)
Precipitation squared	0.0018	0.0021*	-0.0016**	0.0009
	(0.0011)	(0.0010)	(0.0005)	(0.0006)
Soil pH	6512.0350***	6294.7506***	17684.5726***	17449.9187**
	(1952.4530)	(1780.0885)	(4750.6334)	(5185.5948)
Soil Organic Matter	0.4266	39.3916	-1669.7862	-2349.9645
	(530.4450)	(486.4292)	(1656.9560)	(1699.6432)
Available Water Content	1.132e+05**	1.068e+05**	3.307e+05***	2.983e+05***
	(42220.9105)	(39485.5354)	(76048.7195)	(81106.0636)
Population	0.0132	0.0088***	0.0165	0.0133
	(0.0087)	(0.0026)	(0.0126)	(0.0126)
Government Payment	-0.0528	-0.0591	-0.0213***	-0.0197***
	(0.0364)	(0.0376)	(0.0055)	(0.0054)
Corn Yield	-2.5476		-22.2808***	
	(1.3559)		(1.8605)	
Soybean Yield		-10.2188		-87.6929***
		(5.2073)		(7.4483)
County FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.807	0.805	0.865	0.874
Observations	1236	1257	1184	1186

Note: (1) The table shows the combined results of a robustness check by including a crop yield (bu/acre) control to our full model specification (Model 4). (2) For column (1) to (2), the dependent variable is the agricultural land values of states covered by OpTIS project for census year 2007 and 2012. (3) For column (3) to (4), the dependent variable is the agricultural land values of 99 counties in Iowa state for years 2005-2016. (4) Standard errors are clustered by county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A11: Robustness Check: Estimates of the Effects of No-Till Practice on Land Values (AgCensus)

	(1)	(2)	(3)	(4)
No-till pct	7.2963**	7.4798**	8.3268***	12.9825***
	(2.4972)	(2.3869)	(2.1939)	(2.5663)
Time Trend	244.4919***	234.6633***	188.3474***	-888.4094***
	(15.9346)	(14.5200)	(15.0239)	(140.7507)
GDD	-4.2674***	-4.0527***	-3.1986***	-1.4434
	(0.8024)	(0.7768)	(0.7154)	(1.6028)
HDD	-14.3807***	-11.8501***	-15.9402***	-25.6309***
	(3.2828)	(3.0719)	(3.1151)	(4.5442)
Precipitation	-3.4110***	-3.2507***	-0.7435	1.0875
	(0.8665)	(0.8231)	(0.8993)	(1.5565)
Precipitation squared	0.0025**	0.0024**	-0.0001	0.0002
	(0.0009)	(0.0008)	(0.0009)	(0.0011)
Soil pH	4336.8979***	3816.4679**	3022.3963**	2962.8529**
	(1301.4839)	(1271.0928)	(1048.0917)	(1011.0548)
Soil Organic Matter	248.4780	-16.3746	-214.5622	-763.8497
	(432.7612)	(390.7512)	(344.1678)	(619.7701)
Available Water Content	64996.7810*	58422.8742*	53377.1388*	34295.1196
	(28118.8381)	(28231.1032)	(24927.5601)	(31174.1684)
Population	0.0126*	0.0191**	0.0169**	0.0133
	(0.0063)	(0.0060)	(0.0057)	(0.0085)
Agricultural Returns	0.0148***	0.0152***	0.0150***	0.0090***
	(0.0010)	(0.0010)	(0.0010)	(0.0026)
Government Payment	-0.0642	-0.0610		0.0332
	(0.0434)	(0.0429)		(0.0420)
Total Cropland Acres	0.0005			
	(0.0013)			
EQIP Payment		-12.2087***		
		(2.4572)		
Federal Direct Payment			-0.1046**	
			(0.0359)	
Conservation Payment			0.0001	
			(0.0001)	
Crop Insurance Payment			0.0487***	
			(0.0049)	
Interest rate				-2508.0287***
				(330.6302)
County FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.869	0.870	0.895	0.919
Observations	1240	1251	1239	310

Note: (1) The table shows the combined results of robustness checks for AgCensus dataset by including more controls to our full model specification (Model 4). (2) For column (1), we add total cropland acre to our main specification. For column (2), we add EQIP payment to control for payments from federal cost-share programs. For column (3), instead of using government payment variable from the BEA, we use federal government direct payment(total government payment-conservation payment), conservation payment, and crop insurance payment to control for the government payment (for census year 2007 and 2012). For column (4), we add a state-level interest rate for 4 states: KS, MO, OK, and NE.(3) Standard errors are clustered by county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A12: Robustness Check: Estimates of the Effects of No-Till Practice on Land Values (AgCensus)

	(1)	(2)	(3)
No-till pct	6.7403**	8.0739***	5.6044*
	(2.2077)	(2.4066)	(2.5463)
Time Trend	196.2533***	248.1015***	262.4898***
	(17.0442)	(16.1986)	(16.6960)
GDD	-2.7802***	-3.8937***	-2.9469***
	(0.7542)	(0.7827)	(0.8210)
HDD	-19.6430***	-11.2517***	-5.3101
	(3.0709)	(3.1294)	(3.7788)
Precipitation	-0.9659	-3.0163***	-3.1032***
	(0.8407)	(0.8222)	(0.8266)
Precipitation squared	0.0001	0.0021*	0.0023**
	(0.0008)	(0.0008)	(0.0008)
Soil pH	3596.8581**	3760.7296***	4002.4844***
	(1143.4707)	(1049.9877)	(1066.0717)
Soil Organic Matter	216.5141	263.8290	305.8817
	(417.7962)	(370.4037)	(371.6056)
Available Water Content	56573.8708*	62634.9929**	72288.9290**
	(25195.3792)	(23248.2419)	(24992.2046)
Population	0.0162**	0.0123**	0.0091*
	(0.0063)	(0.0046)	(0.0043)
Agricultural Returns	0.0146***	0.0150***	0.0145***
	(0.0011)	(0.0010)	(0.0010)
Government Payment	-0.0533	-0.0477	-0.0712
	(0.0381)	(0.0417)	(0.0417)
Crop Insurance Indemnity	0.0168***		
	(0.0020)		
Average Coverage Level		-3050.2884*	
		(1298.6618)	
Insured Acres pct			-1047.1873***
			(281.1928)
County FE	Yes	Yes	Yes
Adjusted R^2	0.891	0.868	0.870
Observations	1240	1265	1265

Note: (1) The table shows the combined results of robustness checks for AgCensus dataset by including more crop insurance participation controls to our full model specification (Model 4). (2) For column (1), we add crop insurance indemnity ('000 \$) to our main specification. For column (2), we add average crop insurance coverage level (%) for each county. For column (3), we add the percentage of insured acres (%) at county-level. (3) Standard errors are clustered by county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A13: Robustness Check: Estimates of the Effects of No-Till Practice on Land Values (Iowa State)

	(1)	(2)	(3)
No-till pct	4.5926*	5.0553*	2.8132
	(2.1238)	(2.2692)	(6.3411)
Time Trend	605.9947***	602.6599***	1168.0072***
	(12.9738)	(12.9966)	(86.5749)
GDD	2.6584***	2.7712***	1.8253
	(0.1838)	(0.1850)	(2.2964)
HDD	-43.9077***	-49.7856***	-75.9541***
	(7.3790)	(7.7806)	(19.2640)
Precipitation	-2.0979**	-1.7101*	4.5189
	(0.6794)	(0.7070)	(3.4544)
Precipitation squared	-0.0002	-0.0005	-0.0003
	(0.0005)	(0.0005)	(0.0033)
Soil pH	10561.0673**	11564.6362**	12233.4974**
	(3805.8225)	(3793.8567)	(4054.7450)
Soil Organic Matter	-600.3935	-30.2284	2801.4440
	(1278.2921)	(1426.5723)	(1728.1437)
Available Water Content	2.393e+05***	2.771e+05***	3.008e+05***
	(58613.1602)	(63501.8571)	(73625.4915)
Population	0.0124	0.0176	0.0182
	(0.0111)	(0.0105)	(0.0103)
Agricultural Returns	0.0103***	0.0101***	0.0091***
	(0.0010)	(0.0010)	(0.0026)
Government Payment	-0.0122**	-0.0116**	
	(0.0036)	(0.0038)	
Total Cropland Acres	-0.0225***		
	(0.0049)		
EQIP Payment		-9.9897	
		(33.0607)	
Federal Direct Payment			-0.1064
			(0.0562)
Conservation Payment			0.4299**
			(0.1512)
Crop Insurance Payment			0.0268**
			(0.0096)
County FE	Yes	Yes	Yes
Adjusted R^2	0.916	0.911	0.983
Observations	1087	1087	198

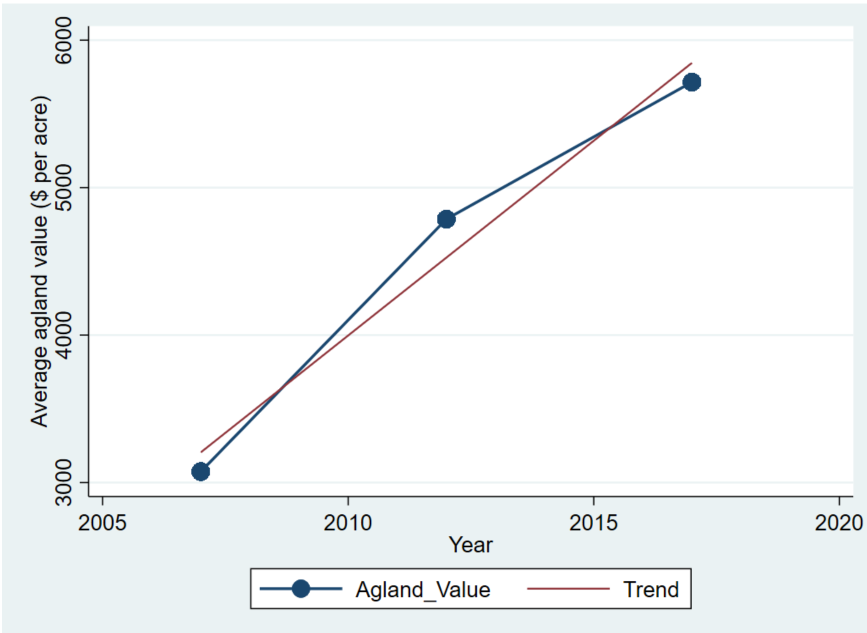
Note: (1) The table shows the combined results of robustness checks for Iowa dataset by including more controls to our full model specification (Model 4). (2) For column (1), we add total cropland acre to our main specification. For column (2), we add EQIP payment to control for payments from federal cost-share programs. For column (3), instead of using government payment variable from the BEA, we use federal government direct payment(total government payment-conservation payment), conservation payment, and crop insurance payment to control for the government payment (for census year 2007 and 2012). (3) Standard errors are clustered by county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A14: Robustness Check: Estimates of the Effects of No-Till Practice on Land Values (Iowa State)

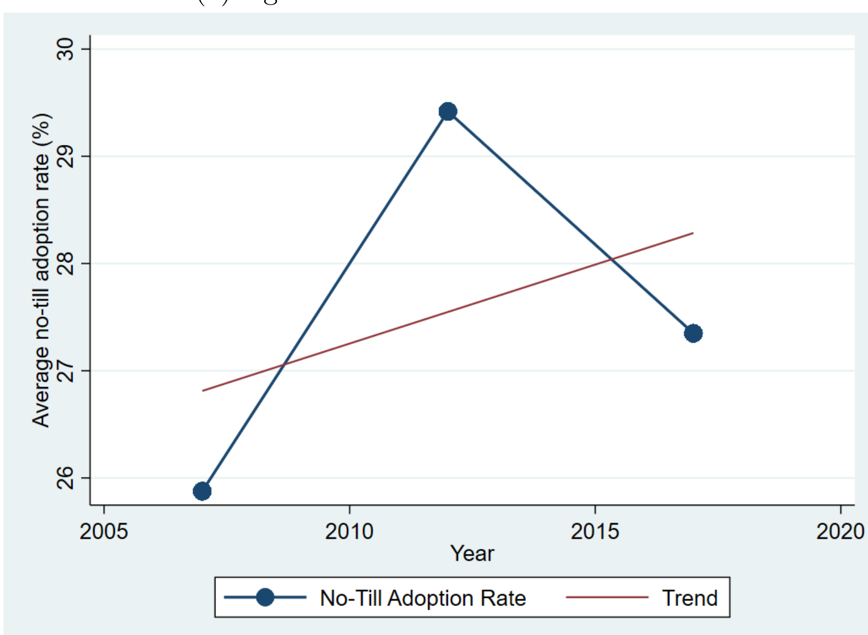
	(1)	(2)	(3)
No-till pct	2.7002	6.2346**	4.9651*
	(1.9409)	(2.3415)	(2.2410)
Time Trend	558.3813***	521.2335***	595.6216***
	(12.5438)	(31.5120)	(14.6093)
GDD	2.5645***	2.8500***	2.8043***
	(0.1731)	(0.1969)	(0.1922)
HDD	-50.2596***	-50.7497***	-49.4809***
	(7.1137)	(8.0855)	(7.7627)
Precipitation	1.1924*	-1.8111**	-1.6199*
	(0.5435)	(0.6879)	(0.7133)
Precipitation squared	-0.0025***	-0.0003	-0.0005
	(0.0004)	(0.0005)	(0.0005)
Soil pH	11639.6022**	11183.2035**	11507.5091**
	(3726.4241)	(3587.8703)	(3902.9223)
Soil Organic Matter	-833.6718	338.8463	164.7890
	(1486.6026)	(1462.9173)	(1502.5808)
Available Water Content	2.512e+05***	2.650e+05***	2.715e+05***
	(65967.4673)	(65695.3905)	(67347.3950)
Population	0.0223*	0.0169	0.0174
	(0.0102)	(0.0113)	(0.0106)
Agricultural Returns	0.0099***	0.0116***	0.0102***
	(0.0009)	(0.0013)	(0.0010)
Government Payment	-0.0033	-0.0122**	-0.0121**
	(0.0031)	(0.0039)	(0.0040)
Crop Insurance Indemnity	0.0359***		
	(0.0020)		
Average Coverage Level		82.6740**	
		(29.9868)	
Insured Acres pct			6.8158
			(8.5344)
County FE	Yes	Yes	Yes
Adjusted R^2	0.934	0.912	0.911
Observations	1087	1089	1089

Note: (1) The table shows the combined results of robustness checks for Iowa dataset by including more crop insurance participation controls to our full model specification (Model 4). (2) For column (1), we add crop insurance indemnity ('000 $) to our main specification. For column (2), we add average crop insurance coverage level (%) for each county. For column (3), we add the percentage of insured acres (%) at county-level. (3) Standard errors are clustered by county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A1: Study area: Mapping by OpTIS was done on 645 counties (yellow) and this area covers 12 states in the US Midwest (Source: Hagen et al. (2020)).

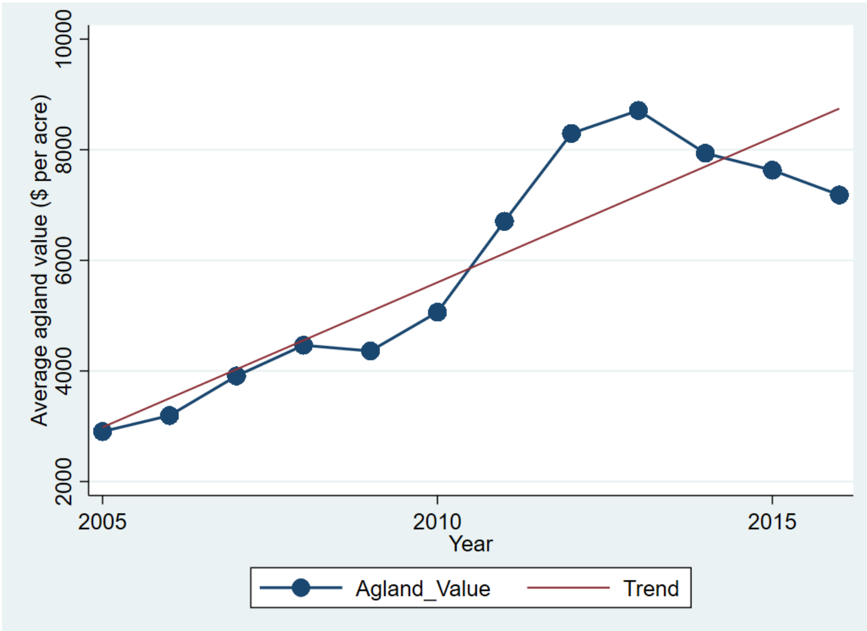


(a) Agricultural land values over time

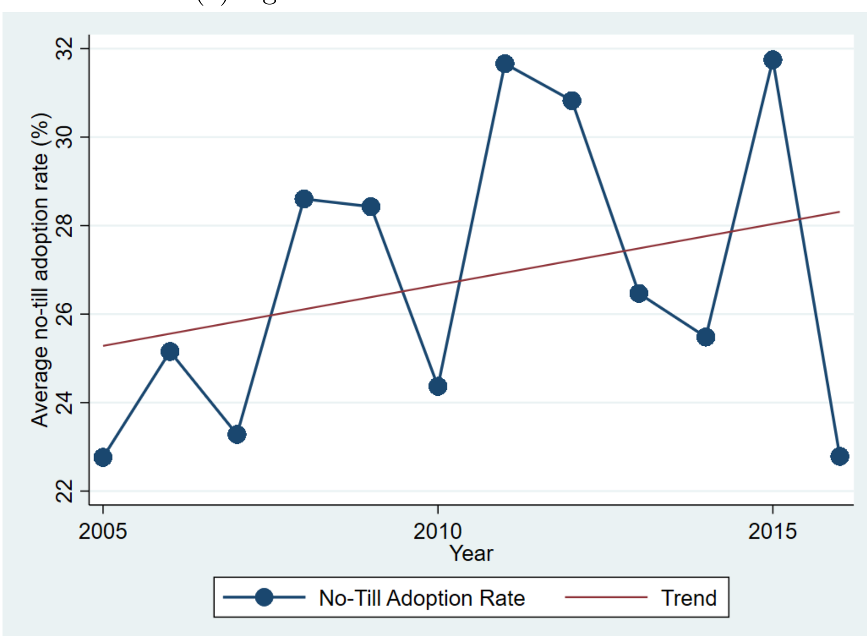


(b) No-till practice adoption rate over time

Figure A2: Year-to-Year Variation in Agricultural Land Value and No-Till Practice Adoption Rate (Census data)



(a) Agricultural land values over time



(b) No-till practice adoption rate over time

Figure A3: Year-to-Year Variation in Agricultural Land Value and No-Till Practice Adoption Rate in Iowa

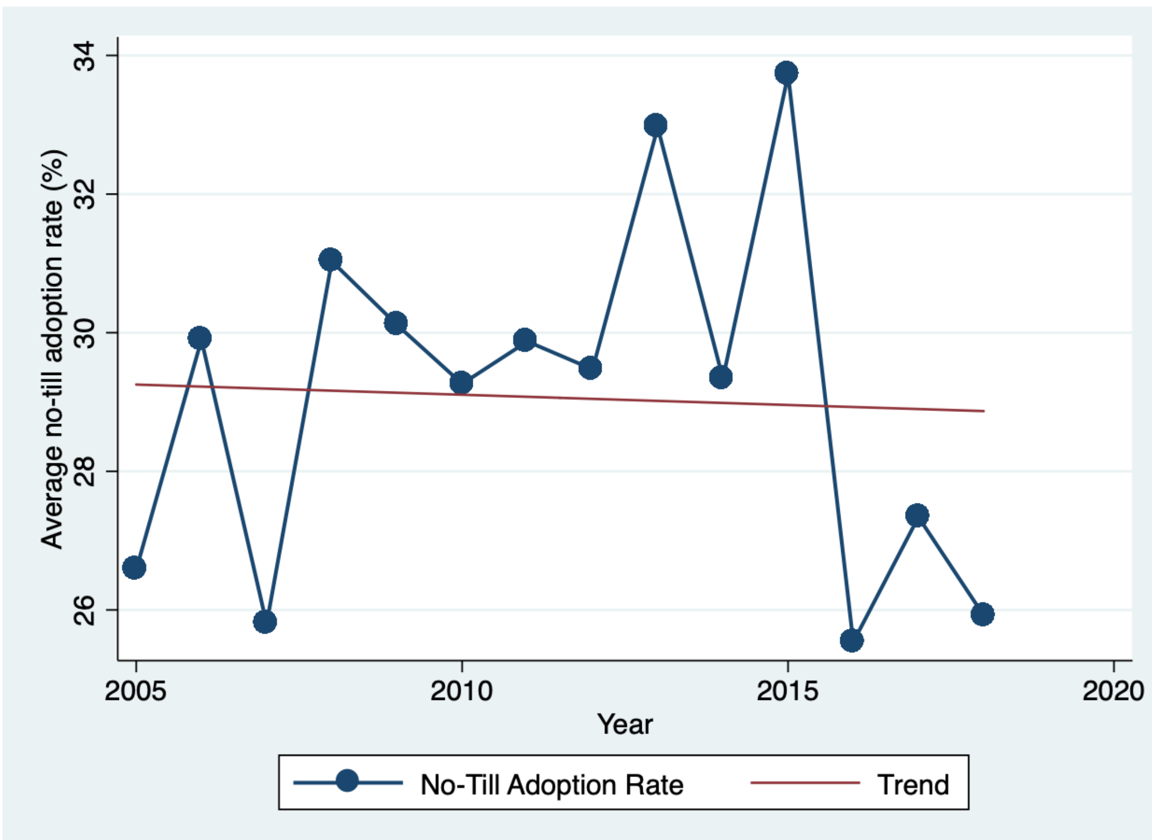
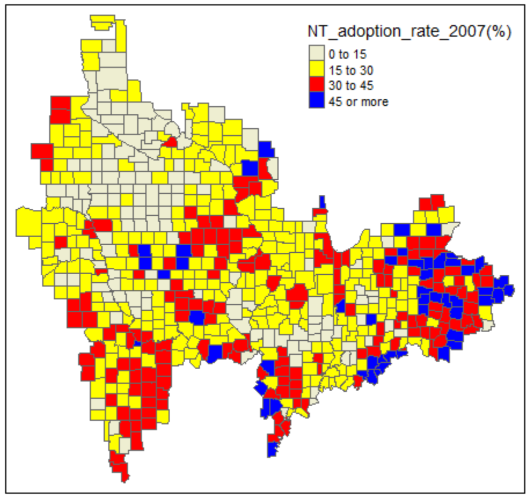
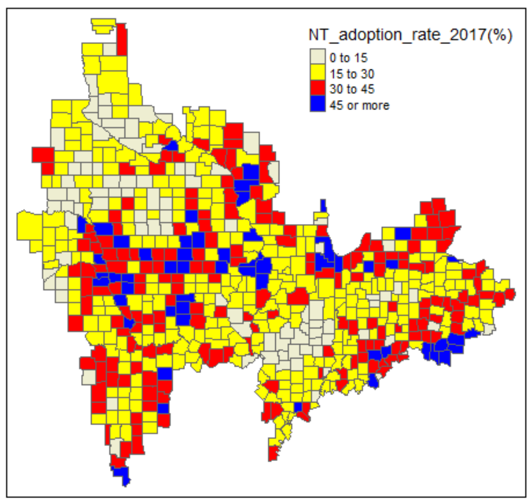


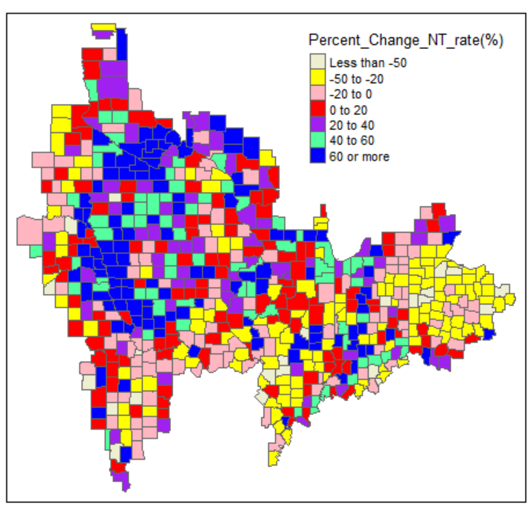
Figure A4: Year-to-year variation of no-till adoption rates for OpTIS data from 2005 to 2018



(a) No-Till adoption rate in 2007

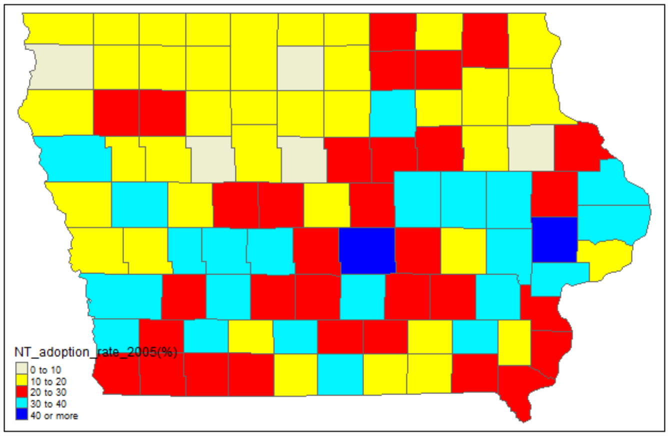


(b) No-Till adoption rate in 2017

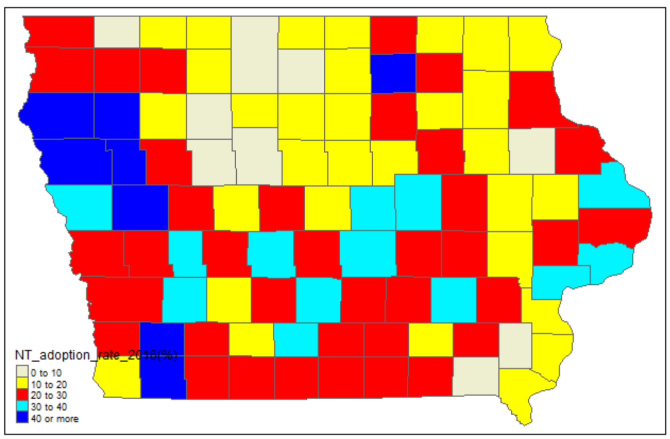


(c) Percentage Change in no-till adoption rate

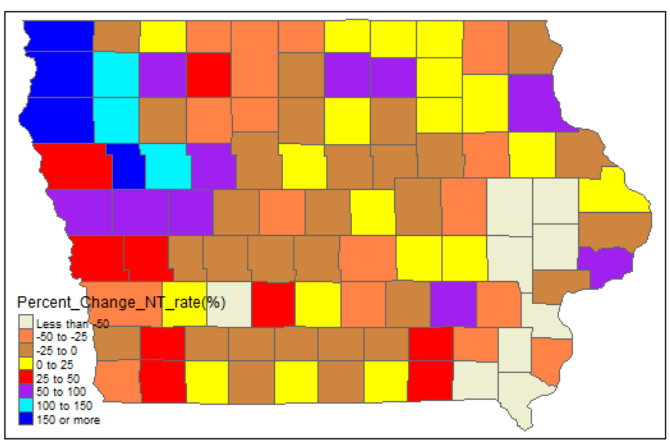
Figure A5: County-level variation in no-till adoption rate from 2007 to 2017 (AgCensus)



(a) No-Till adoption rate in 2005

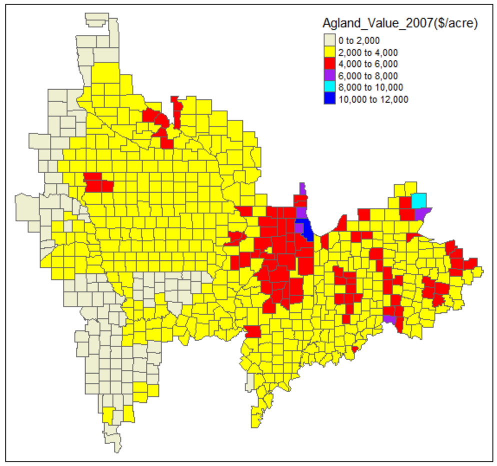


(b) No-Till adoption rate in 2016

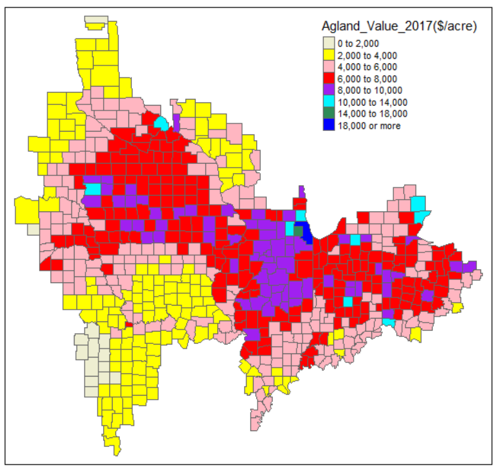


(c) Percentage Change in no-till adoption rate

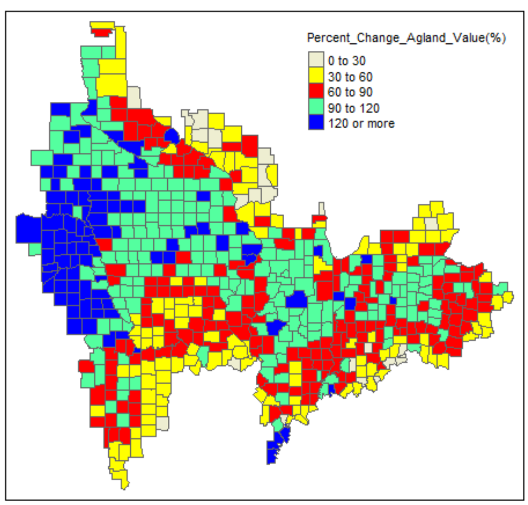
Figure A6: County-level variation in no-till adoption rate from 2005 to 2016 (Iowa)



(a) Agricultural land value in 2007

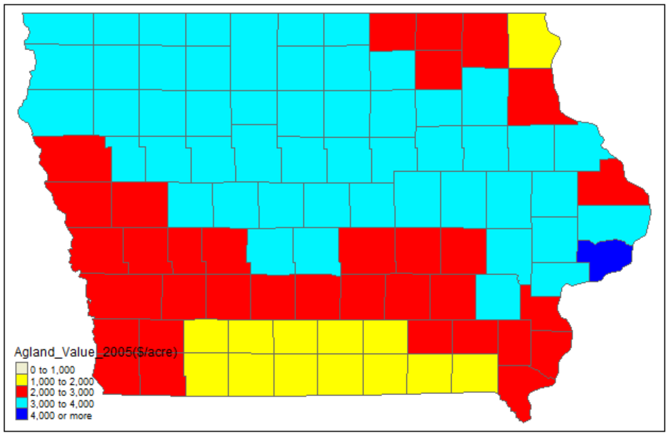


(b) Agricultural land value in 2017

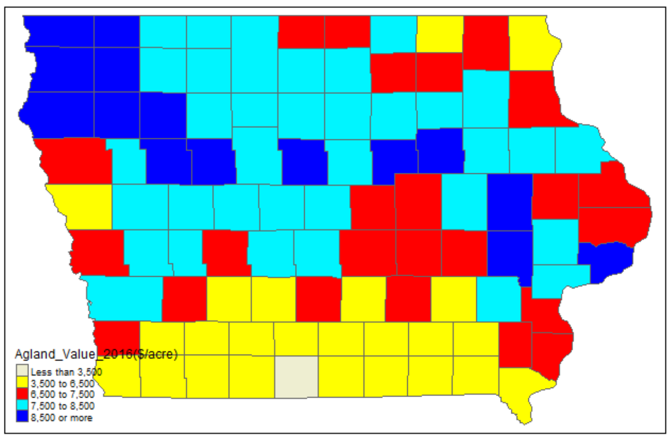


(c) Percentage Change in agricultural land values

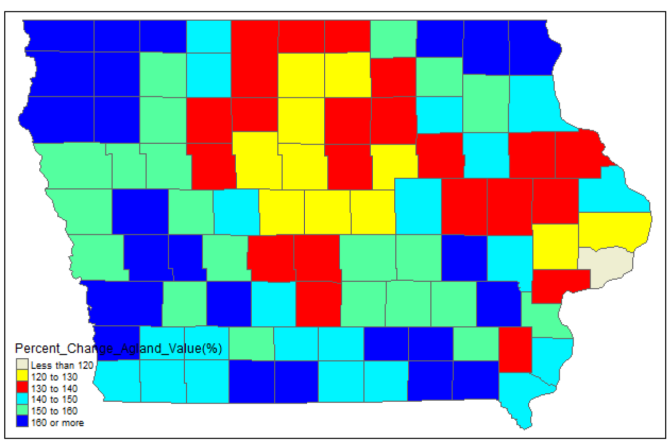
Figure A7: County-level variation in agricultural land values from 2007 to 2017 (AgCensus)



(a) Agricultural land value in 2005



(b) Agricultural land value in 2016



(c) Percentage Change in agricultural land values

Figure A8: County-level variation in agricultural land values from 2005 to 2016 (Iowa)