Peer Effects in the Diffusion of Water Saving Agricultural Technologies

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Selected Paper prepared for presentation at the 2018 Agricultural & Applied Economics Association Annual Meeting, Washington, D.C., August 5-August 7

Title

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JEL Codes: O33, Q15, Q16, Q25, R11

Keywords: Agriculture, Efficient Irrigation, Energy, Groundwater, High Plains Aquifer, Peer Effects, Technology Adoption, Water Saving Technology

Abstract

We investigate the role of peer effects in the diffusion of an important water saving irrigation technology: Low Energy Precise Application (LEPA). Using detailed irrigation behavior data for growers in the High Plains Aquifer region of Kansas covering 1990-2014, we find clear evidence of peer influence in adoption of LEPA, net of environmental factors. Specifically, an additional neighboring LEPA installation within 1 km increases the probability of adoption by 0.2 percentage points, on average, and this effect diminishes with distance. Our empirical estimates indicate that in the absence of peer effects LEPA adoption would have been about 10 percent lower (1,000-1,700 fewer installations) per year. In addition, we find that growers install LEPA in response to higher energy prices.

Irrigated water is a fundamental input to agricultural production in many parts of the world. Agricultural water use accounts for approximately 80% of global freshwater resource consumption (Jury and Vaux, 2005), with 40% of this water being sourced from aquifers. However, growing dependence of agricultural production on groundwater is causing rapid depletion of large aquifers, especially in Asia and the United States. Between 1960 and 2000, global groundwater depletion is estimated to have doubled (Wada, et al., 2010). In the United States, depletion of the High Plains Aquifer and California's Central Valley are particularly problematic (Scanlon, et al., 2012). In light of these concerns, policy makers have sought to encourage the adoption of water-saving irrigation technologies, which are often cited as being an important component of meeting water conservation goals.

This paper examines spatial-temporal patterns of adoption of an important type of water saving irrigation technology: Low Energy Precise Application (LEPA). Our study area is the Kansas portion of the High Plains Aquifer. Among the factors we investigate, we place a particular focus on the possibility of peer effects as a driver of LEPA adoption. Recently, several studies have documented causal peer effects in settings such as residential solar photovoltaic installations (Bollinger and Gillingham, 2012, Müller and Rode, 2013, Graziano and Gillingham, 2015, Rode and Weber, 2016), healthcare products (Oster and Thornton, 2012), residential foreclosures (Towe and Lawley, 2013), and exploitation of natural resources (Lynham, 2017, Sampson and Perry, 2017).[1] Another strand of literature has studied peer effects in the adoption of certain agricultural technologies (Foster and Rosenzweig, 1995, Bandiera and Rasul, 2006, Conley and Udry, 2010,

[1] Sampson and Perry (2017) investigate peer effects in the appropriation of rights to groundwater in the Kansas High Plains Aquifer using data back to 1943.

Ramirez, 2013, Genius, et al., 2014, Krishnan and Patnam, 2014). However, the only study focused on the role of peer effects in the adoption of water-saving irrigation technology is Genius et al. (2014), who use data from Greece.[2]

For our analysis, we use data from one of the most agriculturally important aquifer systems in the world. Kansas is a top 10 national producer of wheat, grain sorghum, and grain corn and the High Plains Aquifer is the main source of groundwater for the Great Plains region of the United States (i.e "Breadbasket of the World"). A unique aspect of our research is the rich spatial and temporal variation in the irrigation technology adoption data we use. Location-specific data on the adoption of LEPA technology in Kansas over a 25-year period (1990-2014) are obtained from the Water Information Management and Analysis System (WIMAS) of the Kansas Division of Water Resources. Our data and unit of analysis is at the water right level, which is in contrast to some previous studies of peer effects which aggregate adoption observations up to discrete spatial units.

If peer effects do in fact drive decisions to adopt water-saving irrigation technologies, then policy makers can leverage peer influence to steer public expenditures on incentive programs (e.g. Environmental Quality Incentives Programs (EQIP)) where they are most efficient. State and national cost-share programs that subsidize conversion to higher efficiency irrigation have not yet achieved intended reductions in water use (Pfeiffer and Lin, 2014a, Kim and Guilfoos, 2016), suggesting there may be need for more nuanced approaches that account for the social factors underlying adoption decisions. Consider, for example, if decisions to acquire water saving technologies are completely independent of social influences. Then the impact of a regional-

[2] Sangtaek et al. (2008) evaluate the profitability of LEPA adoption for a representative farm in Texas but do not consider the role of peers in individual adoption decisions.

specific incentive program would be confined to that region; there would be no spillover effects. Ex ante analysis of the efficacy of policies to encourage technology adoption are thus flawed if peer effects or other spatial dispersion processes are present but unaccounted for by analysts.

We exploit detailed spatial and temporal variation in reported use of LEPA irrigation in the Kansas High Plains Aquifer in order to separately identify peer effects from other confounding factors. Specifically, we estimate how the relative odds of adopting LEPA change depending on the number of previous LEPA users within a grower's peer network. We define a grower's peer network using spatial bands around the location of a water right. This flexible measure of the peer network reduces the possible measurement error bias or modifiable areal unit problem associated with using rigid borders (Fotheringham and Wong, 1991) and allows us to explicitly test for peer influence dissipating over distance. To control for the possibility of peer self-selection, we include a rich set of county and agricultural district fixed effects. Year fixed effects and agricultural district by year fixed effects are included to control for time-varying correlated unobservables (e.g. trends in LEPA use unrelated to peer influence). Finally, simultaneity in LEPA adoption is not a concern because we use the number of previously installed LEPA systems as the measure of peer influence (Bollinger and Gillingham, 2012, Sampson and Perry, 2017). In addition to peer effects, we estimate the impacts of a rich set of climate, hydrology, and energy price data, which are spatially merged to LEPA use data.

Overall, we find clear evidence of peer effects (i.e. spatial neighboring effects) from previous adoption of LEPA. By using spatial bands of differing radii, we are able to explicitly detect a pattern of spatial neighboring effects that diminish over space. For example, our results indicate that one more LEPA installation within 1 km increases the probability of LEPA adoption by about 0.2 percentage points, on average. By comparison, a LEPA adoption that takes place 2-5 km away increases the probability of adoption by only 0.05 percentage points on average. Additionally, we find that growers who planted water intensive crops (e.g. corn, soybeans, alfalfa), irrigated a large number of acres, or who ran irrigation pumps for many hours in the previous year are more likely to install LEPA. We also find that growers install LEPA in response to higher energy prices. These results are robust to alternative estimation techniques using individual water right fixed effects and random effects. In contrast to recent literature (e.g. Schuck, et al., 2005), we find no evidence of adverse long run climate nor short run weather conditions affecting farmer's decisions to install LEPA. Finally, we illustrate the policy implications of our estimates by simulating a counterfactual LEPA adoption curve with no peer effects. Using the counterfactual, we find that ignoring peer effects results in under estimating LEPA adoption by about 10-12 percent in most years. This corresponds to about 1,000-1,700 fewer LEPA installations per year over the last 14 years of analysis (2001-2014).

The remainder of the article is organized as follows. In Section 1, we provide background on LEPA in Kansas. In Section 2, we present our data sources and summarize our detailed dataset of LEPA use in Kansas. In Section 3, we describe our empirical approach. Section 4 presents results from the empirical analysis, documenting the primary factors that influence LEPA adoption. Section 5 presents robustness checks and alternative specifications. In Section 6, we demonstrate the role of peer effects in LEPA adoption by estimating cumulative adoption curves with and without peer effects. The article closes with discussion and interpretation of our findings.

1. Background

Our study area is the state of Kansas, where production agriculture relies heavily on groundwater irrigation from the High Plains Aquifer. Kansas ranks in the top 10 nationally in wheat, grain sorghum, and grain corn production (Kansas Department of Agriculture, 2015). Irrigation water withdrawals from the Kansas High Plains Aquifer are about 3.5 million acre-feet annually, which are used to irrigate about 3 million acres. Recharge of the aquifer is low relative to the annual withdrawals and secure water availability for agriculture is a significant concern.

Early agricultural irrigation in Kansas was typified by flood irrigation. Center pivot irrigation, which was conceived in 1949 by Frank Zybach, came into general use during the 1960's and revolutionized irrigation technology at the time. A center pivot irrigation system is a pipe structure that rotates about a central pivot point, which is connected to a water supply. Irrigation water is broadcast to plants via a network of sprinkler packages along the pipe. In 1970, it is estimated that about 18 percent of the 1.8 million irrigated acres in Kansas were sprinkler irrigated with center pivots (Rogers and Lamm, 2012). Between 1970 and 1980, the amount of irrigated land in Kansas increased by approximately 1 million acres, largely owing to the adoption of center pivot irrigation (Rogers and Lamm, 2012). At present, most of the irrigated land in Kansas uses some form of center pivot technology.

Water delivery packages can be composed of devices ranging from conventional sprinklers to more modern drip tubes or dropped nozzles. The latter delivers water more directly to the soil surface and can be equipped with low flow emitters. Moreover, dropped nozzle packages (also referred to as LEPA) require very low pressure to operate[3], thus saving energy required for water delivery, and increasing the efficiency of irrigation by decreasing water lost to evaporation or drift. While standard center pivot sprinkler water use efficiency is about 80-90 percent, efficiencies of center pivot coupled with LEPA are upward of 95 percent (Schneider, 2000).

[3] Reduction from 75 psi for standard center pivot to 18 psi for LEPA (DeLano, et al., 1997).

Recognizing the problem of declining aquifer levels, the state of Kansas spent nearly $20 million on programs such as EQIP to incentivize the adoption of more efficient irrigation technologies between 1997 and 2014.[4] These programs provided cost sharing to farmers for the purchase and installation of irrigation technology upgrades, with some of the money being used for LEPA conversions (US Department of Agriculture, 2006). Figure 1 shows the number of new LEPA installations per year and the cumulative adoption curve for the Kansas portion of the High Plains Aquifer. Total conversion to LEPA has followed the well-known S-curve of technology adoption noted by Griliches (1957). As of 2014, there are nearly 16,000 water rights over the Aquifer that have experimented with LEPA. Moreover, the spatial pattern of LEPA adoption has followed a pronounced clustering over time, where new LEPA installations seem to occur in areas where LEPA is already being used by others (figure 2).

2. Empirical Framework

Background

Our econometric framework draws on two strands of literature. The first strand concerns irrigation technology choice. Since the work of Caswell and Zilbermann (1985), numerous studies have investigated the factors that influence the type of irrigation system chosen by agricultural producers. A common thread in these studies is that the choice of irrigation technology is modeled as a discrete choice that depends on energy costs, field characteristics, aquifer characteristics, and, more recently, climate (Green, et al., 1996, Schuck, et al., 2005, Koundouri, et al., 2006). There

[4] We thank Lisa Pfeiffer and personnel at the Kansas Natural Resource Conservation Service for data access.

are only three previous studies to model conversion to LEPA. Sangtaek et al. (2008) evaluate the profitability of LEPA under different output prices. Pfeiffer and Lin (2014a) estimate the factors that affect Kansas LEPA adoption in the first stage of a two-stage groundwater extraction model. Li and Zhao (2018) compare water use by Kansas LEPA adopters to water use by growers having conventional irrigation.

We specify an empirical framework in the tradition of previous studies by modeling the decision to adopt LEPA in a discrete choice framework with a profit maximization objective. In particular, let π_0 denote perceived present and future profits without LEPA and π_1 denote perceived present and future profits with LEPA. A producer converts to LEPA when

$$\pi_1 > \pi_0. \tag{1}$$

Furthermore, profits can be specified to depend on various characteristics and factors: that is, we can write $\pi(x)$, where x is a vector of characteristics and variables.

The second strand of studies is the social interaction literature. As noted, this literature encompasses a wide range of topics, from residential solar photovoltaic installations (e.g. Bollinger and Gillingham, 2012) and healthcare products (Oster and Thornton, 2012) to residential foreclosures (Towe and Lawley, 2013) and various agricultural technologies (Foster and Rosenzweig, 1995, Bandiera and Rasul, 2006, Conley and Udry, 2010, Ramirez, 2013, Genius, et al., 2014, Krishnan and Patnam, 2014). For the purpose of this study, there are three issues identified by the peer effects literature that are pertinent to our empirical model. The first is how to define an individual's peer group. Previous studies either elicit detailed information from individual respondents about who their peers are (e.g. Genius, et al., 2014) or, more commonly, peer groups are inferred based on spatial or situational proximity. In our data, we observe water rights holders' locations, but no information about who their peers are. Thus, we define peer groups based on spatial distance. This presents the additional issue of what distance to use. Here we take a flexible approach by estimating peer effect across three different radii: (i) 0-1 km, (ii) 1-2 km, and (iii) 2-5 km (see figure A1). To put these distances in perspective, the average irrigated acreage for a water right holder is about 160 acres (i.e. a quarter-section, 0.8km×0.8km). Defining peer groups in this way, rather than on the basis of predefined geographical boundaries, reduces the possibility for boundary issues, while also permitting us to estimate whether peer effects diminish with distance (as would be expected).

The second issue is how to empirically model peer effects. Following the arguments by Bollinger and Gillingham (2012), we incorporate peer effects using the installed base approach. In our context, the installed base is defined as the stock of neighbors up to the previous period that have adopted LEPA. Specifically, let i denote an individual, t denote a year, and $g[i]$ denote the set of individual i's neighbors. The installed base is defined as

$$y_{i(t-1)} = \sum_{h \in g[i]} D_{h(t-1)} \tag{2}$$

where $D_{h(t-1)} = 1$ if individual h in peer group $g[i]$ had converted to LEPA at or before year $(t-1)$. Irrigation upgrades are most typically conducted in spring prior to planting (Jonathan Aguilar, personal communication, February 7, 2018). Thus, the installed base is appropriate in our context because there will typically be a lag between the moment that farmers observe their neighbors' positive adoption decision(s) and the moment that they fully install LEPA. Moreover, by using the installed base as a measure of peer effects, we address the simultaneity issue noted by Manski (1993).

The final insight from the social interaction literature concerns the identification of peer effects. The fundamental issue is that an individual may display similar behavior to his or her peers either because of causal spillover peer effects or because they are exposed to the same environmental factors. The latter set of factors are commonly called contextual effects. Failure to control for contextual effects may result in a biased peer effect estimate. For example, Cohen and Fletcher (2008) found that in using standard econometric techniques to control for contextual effects, a previously identified positive peer effect associated with obesity disappeared. We control for contextual factors by including a rich set of climate, hydrology, soil and other field characteristics. Because our dataset is a panel (in contrast to many previous studies on the adoption of irrigation technologies), we can also control for both time-invariant and time-varying unobserved heterogeneity through spatial and year-specific fixed effects.

Econometric Model

Suppose we observe $i = 1,...,N$ water rights holders. Each water rights holder is observed for $t = 1,...T_i$ years, where T_i is either the year that individual i adopted LEPA or, if individual i never adopted LEPA, the final time period in our sample (2014).[5] Normalizing π_0 (perceived profits without LEPA) to zero, and indexing profits by i and t, the perceived present and future profits associated with conversion to LEPA is written as π_{it}. In each year t individual i chooses whether or not to install LEPA, indexed by d_{it}, on the basis of profit maximization:

$$d_{it} = \begin{cases} 0 & \pi_{it} \le 0 \\ 1 & \pi_{it} > 0 \end{cases} \tag{3}$$

Profits are specified to depend on the installed base and various spatial and temporal characteristics:

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[5] As an example, if a water rights holder adopts LEPA in 2001, they then drop out of the dataset from 2002 and on. Note, however, that their positive adoption decision contributes to the installed base for the remainder of the sample.

$$\pi_{it} = \underbrace{\sum_{r\in\Gamma} \delta_r y^r_{i(t-1)} + \beta' x_{it} + \alpha' z_{i(t-1)} + \eta_c + \tau_t}_{v_{it}} + \varepsilon_{it} \tag{4}$$

where $y^r_{i(t-1)}$ is the installed base in sub-radius $r \in \Gamma$ (where $\Gamma \equiv \{\text{0-1km,1-2km,2-5km}\}$); x_{it} is a vector of contemporaneous characteristics; $z_{i(t-1)}$ is a vector of lagged characteristics, and η_c and τ_t are spatial and time effects, respectively. The vector x_{it} includes various soil, hydrology, climate, energy cost, and field characteristics, the details of which are provided below. The vector $z_{i(t-1)}$ includes binary variables for whether a choice-maker previously cultivated a water intensive crop (corn, soybeans, or alfalfa) and for whether they previously used a center pivot system. The vector $z_{i(t-1)}$ also includes non-binary variables such as the number of acres irrigated and total hours of pumping. Year fixed effects, τ_t, are included in all specifications and county level fixed effects (η_c) are included in two of four specifications. Year fixed effects control for statewide factors that influenced the returns to LEPA, and spatial fixed effects control for time-invariant unobserved spatial heterogeneity in the returns to LEPA. In one specification, we also include year fixed effects for each of the five agricultural district in the High Plains Aquifer, which capture regional-specific temporal shocks that affect LEPA adoption.

The model is completed with an assumption on the distribution of the unobservable component, ε_{it}, which we assume is IID and follows the type I extreme value distribution. The probability of converting to LEPA is therefore given by the standard logit expression

$$p_{it} = \frac{e^{v_{it}}}{1 + e^{v_{it}}} \tag{5}$$

The likelihood function is given by the product of the probabilities for the observed adoption decisions of Kansas water rights holders:

$$L = \prod_{i=1}^{N} \prod_{t=1}^{T_i} p_{it}^{\;d_{it}} (1 - p_{it})^{(1-d_{it})} \tag{6}$$

The vector of model parameters, ($\alpha, \beta, \lambda, \tau$), is estimated via maximum likelihood.

While we are able to control for a rich set of factors that are likely to influence grower decisions to adopt LEPA, there is still a possibility for unobservable characteristics. For instance, some growers may be more inclined to technological experimentation due to age or educational attainment. In our data, we observe over 18,000 decision makers and 25 periods. Attempting logit specification with controls at the individual grower level introduces the problem of incidental parameters and biased estimates, given the number of individuals far exceeds the time periods (Greene, 2004). We therefore test the robustness of the logit estimates by estimating linear probability models controlling for individual heterogeneity with fixed and random effects in later sections.

3. Data

The data used for our estimation are drawn from multiple sources. Information about water rights identifications, well locations, water rights priority dates, irrigation behavior, and irrigation technology for the years 1990-2014 come from the Water Information Management and Analysis System (WIMAS), which is maintained by the Kansas Division of Water Resources. The unit of analysis is at the level of a water right, with each water right treated as a single grower. We use the water right as the unit of analysis rather than the well to avoid the complicated situation where a single well is shared by multiple water rights. For approximately 35 percent of the data, a single water right is associated with a single well. Over 90 percent of the data is made up of water rights having five or fewer wells. For water rights having multiple wells, we determine a central location by calculating mean coordinates (consistent with methods used for calculating well spacing requirements per K.A.R. 5-4-4.). In total, there are 18,486 unique water right identifications in our data.

In Kansas, it is possible for individuals to hold multiple water rights. If an individual with multiple water rights in close proximity serially acquires LEPA, then this would produce a spatial-temporal clustering that would appear to be a peer effect. To avoid this possibility, we obtain a recent list of contact names and addresses for groundwater rights in Kansas. In total, we obtain information for 9,067 unique name, address combinations. It is likely that water rights have been consolidated during the period of our analysis, as most regions of Kansas are either fully appropriated or over-appropriated. However, this should provide a conservative correction for any "own-neighbor" effects. We match the contact list to the 18,486 unique water rights identifications obtained from WIMAS and omit any neighboring water rights listing the same name and address as the focal water right from being treated as a peer.

Soils

Spatially explicit soils characteristics likely to affect the returns from LEPA installation are obtained from the SSURGO soil survey on the website of the USDA Natural Resource Conservation Service (NRCS). These characteristics include detailed information on soil composition, drought vulnerability, and water storability. Our regression specifications include the following soil characteristics as controls: proportion of cropland with pH less than 6 (acidic soils), proportion of cropland with pH greater than 7.5 (basic soils), plant available water storage, soil organic carbon, and a dummy for whether the soils are vulnerable to drought. These soil characteristics were chosen to represent agricultural productivity and water storability.

Soils with a pH less than 6 or greater than 7.5 are known to affect crop yields (USDA Natural Resource Conservation Service, 1998). Positive coefficients on these variables would suggest land quality-augmenting behavior (Lichtenberg, 1989). Greater plant available water storage allows the grower to schedule irrigation activities over longer intervals. We expect negative coefficients on this variable, as conventional center pivot is expected to perform relatively well for longer irrigation schedules. We hypothesize that LEPA is a form of adaptation to heat conditions, and so a positive coefficient is expected on drought vulnerable soil types.

Hydrology

Spatially explicit hydrology characteristics for the High Plains Aquifer are obtained from The Kansas Geological Survey. These variables include the following: hydraulic conductivity, specific yield, average annual recharge, and depth to water at five-year intervals. We smooth the depth to water using linear-spline smoothing. We do not obtain well capacity data. However, well capacity is likely to be a mixed function of depth to water and hydraulic conductivity.

LEPA requires lower pressure to operate than conventional center pivot. Thus, we expect that the benefits of lower water pressure associated with LEPA will accrue most readily to growers located over portions of the aquifer having lower hydraulic conductivity, lower specific yield, and greater depth to water. Therefore, we expect negative coefficients on hydraulic conductivity and specific yield. We expect a positive coefficient on depth to water. If growers adopt LEPA out of concern for future water availability, then this should be reflected by a negative coefficient on average annual recharge.

Climate

Climate data at the county level are obtained from PRISM using the method described in Schlenker and Roberts (2009). We construct four climate variables for each county: ten-year moving averages of precipitation, the number of degree days between 8 and 32 degrees Celsius, degree days greater than 32 Celsius (heat levels that are detrimental to crop growth (Schlenker, et al., 2006)), and a one-year lagged measure of degree days greater than 32 Celsius. One of the principle advantages of LEPA over the conventional center pivot sprinkler system is the reduction in evaporative water losses: with LEPA, irrigation water is applied more directly to the soil surface rather than the canopy (Lyle and Bordovsky, 1983). We therefore hypothesize that detrimental heat exposure is the climate variable of most interest. By including both a ten-year moving average and a lagged measure of detrimental heat, we are able to capture both long-run responses to *climate* conditions and short-run adaptation to *weather*, respectively. A negative coefficient on precipitation and positive coefficient on detrimental heat variables would suggest evidence of LEPA as an adaptation to drought or heat.

Energy

Pumps used to withdraw groundwater in Kansas are powered by natural gas, diesel, or electricity. Of the roughly 3 million acres irrigated from groundwater in Kansas, about 50 percent are serviced by pumps running off natural gas, 25 percent are serviced by pumps running off diesel fuel, and 22 percent are serviced by pumps running off electricity (U.S. Department of Agriculture, 2004). The WIMAS data does not provide the energy source for groundwater pumps. Following Pfeiffer and Lin (2014b), we use the natural gas price as the energy price for farmers located in counties having natural gas production during the years 1990-2014.[6] For counties not having natural gas production, we use an index of electricity and diesel prices. Natural gas and electricity price data are obtained from the Energy Information Administration. Diesel fuel prices are for bulk delivery

[6] Natural gas production data are obtained from the Kansas Geological Survey.

of diesel fuel in the northern Plains, obtained from the Nebraska Energy Office. All energy prices are converted to units of dollars per million btu and are adjusted to 2015 dollars using the Consumer Price Index. Because LEPA operates at much lower pressures than conventional center pivot sprinklers, less pumping energy is required. We hypothesize that growers may adopt LEPA partly to save on energy expenditures and thus a positive coefficient on energy prices is expected.

NRCS subsidies

As noted, the state of Kansas subsidized the adoption of LEPA through EQIP during the 1997-2014 period. We obtain EQIP payment data for irrigation upgrades from the Kansas NRCS for the years 1997-2014 (payments started in 1997). EQIP payments are aggregated at the annual and county level. Contracts with EQIP occur when an individual voluntarily enrolls in the program, but we do not observe payments at this level.[7] In total, nearly $22 million was spent on irrigation upgrade programs. We normalize the annual county-level EQIP payments by dividing the total expenditure by the number of water rights in the county. We expect a positive coefficient on EQIP subsidy payments.

The well location and water right data obtained from WIMAS are matched by county to the soils, hydrology, climate, energy price, and NRCS subsidy data using spatial query functions in QGIS. The sample period used in the analysis is thus 1990-2014. Table 1 presents summary statistics of the variables used in model estimation.

4. Results

[7] To enroll in EQIP, growers must first decide upon an irrigation upgrade such as LEPA. Therefore, enrolling in EQIP does not exclude the possibility for earlier peer influence.

Table 2 presents our primary results using a 1-, 2-, and 5-km radius definition of the peer group. All specifications include year fixed effects to account for unexpected year-to-year variation in LEPA adoption, as well as robust standard errors to account for model misspecification. Column 1 presents a specification with spatial fixed effects for the five Groundwater Management Districts (GMD) in the Kansas High Plains Aquifer to control for aquifer characteristics and water use that cluster within GMDs.[8] Column 2 adds dummies for the five agricultural districts (as defined by the USDA) in High Plains Aquifer portion of Kansas to control for socioeconomic and agricultural factors that may cluster at the agricultural district level. Column 3 uses county-level dummies to control for self-selection of peers and other socioeconomic factors that cluster within counties. Finally, column 4 presents our preferred results, which include county dummies and agricultural district by year fixed effects to flexibly address possibly spatial and time-varying correlation in unobservables.

Looking across specifications, our results indicate clear evidence of spatial neighboring effects in the adoption of LEPA irrigation technologies. All reported coefficients are presented as odds ratios – where the odds of adopting LEPA if the corresponding variable is incremented by one unit are in the numerator and the odds of adopting groundwater if the corresponding variable is not incremented are in the denominator. The coefficients of most interest are the lagged number of adopters. Regardless of whether we include county-specific controls or agricultural district-year controls, the previous stock of LEPA users within 5 km are positive, statistically significant at 0.05

[8] GMDs are local institutions which provide water-use planning and management. The five GMDs were formed between 1973 and 1976 per the GMD Act, K.S.A. 82a-1020 through 82a-1040. Primary groundwater use in the GMDs is for agricultural irrigation.

or better, and of a similar magnitude across specifications. For example, in column 4, the coefficient on the number of neighbors within 1 km indicates that one additional LEPA installation within 1 km increases the odds of adoption by 2.8 percent. For ease of interpretation, we also report average marginal effects at the bottom of Table 2. We find that an additional installation within 1 km increases the probability of LEPA adoption by about 0.2 percentage points on average. Furthermore, the change in the results with distance is intuitive. The coefficients are smaller as the distance between an existing LEPA installation and a potential LEPA adopter increases. The average marginal effect of a neighbor that is 1-2 km away is similar to the effect of a neighbor that is 0-1 km away. But, for installations that are 2-5 km away, the influence is only about 20 percent as large as a neighbor that is 0-1 km away. Our results in this regard are consistent with Rode and Weber (2016), who find that spatial neighbor effects in solar photovoltaic installations are highly localized, with influence contained within 1 km. Our result is in contrast to Graziano and Gillingham (2015), who find no obvious dissipation in neighbor effects with distance.

Our results highlight the role of energy prices on decisions to adopt LEPA. Coefficients on county-level energy prices are positive in all four specifications, but only statistically significant in columns 1-3. The average marginal effect of county-level energy price is positive and statistically significant for all specifications, however.[9] The average marginal effect of a $1 per million btu increase (i.e. about 10% increase) in the energy price on the probability of LEPA adoption is about 0.2 percentage points. This finding builds upon the work of Pfeiffer and Lin

[9] The difference of having a coefficient that is not significant while having a significant marginal effect can occur when calculating marginal effects in nonlinear models (e.g. Dowd, et al., 2014, Li and Zhao, 2018).

(2014b) and Zilberman et al. (2008), who find that rising energy prices will increase the cost of groundwater and thus reduce demand. We complement these previous studies by providing evidence that farmers adapt along technological margins in response to increasing energy prices. We also find some evidence suggesting that the effect of energy prices on LEPA adoption is greater in areas having greater depth to water. While the magnitude of the effect is small, this finding is consistent with pumping costs increasing with lift height.

The total number of neighbors within 5 km (both LEPA adopters and non-adopters) is a measure of farm density. We find that areas that are denser on average have lower odds of adopting LEPA. This suggests that returns to scale are important to adoption because farm density and farm size are likely to be inversely related. Water rights are limited in their maximum annual quantity and rate of diversion. The coefficients on authorized rate and authorized quantity are positive but small in magnitude, suggesting they do not affect LEPA adoption in an economically significant way. Water rights that are more senior have greater odds of adopting LEPA. More senior water rights are less susceptible to ceding their rights during times of shortage and thus their access to irrigation water is more secure. Farmers who have used conventional center pivot irrigation technology in the past have greater odds of eventually adopting LEPA. This makes sense, as LEPA is fundamentally a modification to a center pivot base model. Odds of adopting LEPA go up if a water intensive crop (defined as either corn, soybeans, or alfalfa) was planted in the previous year.

Reliance on groundwater for water and food security is widely predicted to increase as more frequent and intense climate extremes increase variability in precipitation and heat (Taylor, et al., 2013). Whether farmers adapt to these changes has important implications for the necessity and extent of policy designed to mitigate climate change. We find that ten-year averaged measures of precipitation and degree days between 8 and 32 Celsius (i.e. favorable conditions) do not significantly affect conversion to LEPA. The coefficient on ten-year averaged degree days over 32 Celsius is noisy across specifications. In columns 1-3, the coefficient is negative and varies in statistical significance. When agricultural district-year effects are specified, the coefficient changes sign and becomes strongly statistically significant. We interpret these patterns as providing no conclusive evidence that LEPA adoption takes place in response to long run trends in heat stress. We also include a lagged measure of degree days over 32 Celsius to capture short-run adjustments to *weather*. This variable is not statistically significant. In sum, our findings provide no conclusive evidence of LEPA adoption as an adaptation to climate trends or weather events.

For the remaining lagged variables, we find that increased irrigated acreage increases the odds of adopting LEPA in the current period. Likewise, increased lagged pumping hours is associated with greater odds of LEPA adoption in the current period. This suggests some returns-to-scale in LEPA adoption decisions and irrigation water use and is consistent with our earlier finding with respect to farm density. The coefficient on drought vulnerable soil is noisy and is not always statistically significant. Specific yield is negative and statistically significant in columns 3-4, suggesting farmers may use LEPA when faced with materials having poor drainage. Depth to water is negative and significant in three of four specifications. Soil organic carbon is negative and significant at 0.10 or better.

To summarize, we find strong evidence of localized spatial neighbor effects and energy prices influencing decisions to adopt LEPA. Moreover, the influence that a neighboring LEPA installation exerts on a potential adopter decreases with distance. Lastly, our results provide evidence that growers having larger irrigated acres, greater pumping hours, more senior water rights, prior experience with center pivot technologies, and water intensive crops are more likely to adopt LEPA.

5. Alternative specifications

We perform specification checks on our primary results in Table 2 and report them in Tables 3 and 4. Table 3 reports estimates where the effects of spatial neighbors within 0-1 km (column 1), 1-2 km (column 2), and 2-5 km (column 3) are estimated in separate models. A potential concern with the model estimates in Table 2 is that the number of peer adopters within the rings of the concentric spatial buffers will almost always covary in the same direction. The specifications in Table 3 include county dummies and agricultural district by year controls, as in column 4 of Table 2. The results in columns 1-3 of Table 3 are consistent with the results from our preferred specification in Table 2. Comparing marginal effects from Table 3 to the marginal effects in column 4 of Table 2 suggests there is some attenuation to estimates of spatial neighbor effects when the rings of the concentric spatial buffers are estimated simultaneously. We therefore interpret our main results in Table 2 as being conservative estimates.

In Table 4, we report estimates from linear probability models exploring different fixed effects specifications. Logit models can be unreliable and difficult to estimate when individual fixed effects are included, particularly when the number of individuals is large relative to the number of time periods (Greene, 2004). In columns 1 and 2, we report results with water right heterogeneity modeled using a random effect, $c_i \sim N(0, \sigma_c^2)$, with district by year or county by year effects, respectively. In columns 3 and 4, we report results with water right heterogeneity modeled using a fixed effect with district by year or county by year effects, respectively. Thus, the results from columns 1-4 provide information on whether water right level unobserved heterogeneity is a significant concern for our peer effect estimate.

In general, the linear probability results confirm the estimated spatial neighbor effects from the logit model. Coefficient estimates on the 0-1, 1-2, and 2-5 km neighbors generally follow the same pattern of attenuation with distance (0-1 and 1-2 km effects remain similar in magnitude). The linear probability model results produce coefficients that are slightly larger than the average marginal effect estimates from the logit models, suggesting the main results in Table 2 are conservative estimates of spatial neighbor peer effects.

6. Counterfactual simulation

To obtain an approximation of the impact of peer influence on total LEPA usage, we estimate a LEPA adoption curve with and without peer effects using the specification in column 4 of Table 2. We obtain the fitted adoption curve by estimating the predicted probability of LEPA adoption for each water right in each year, then take the average annual predicted probability across water rights, and multiply that average probability by the number of potential adopters in that year. The counterfactual adoption curve is found by setting the 0-1 km, 1-2 km, and 2-5 km peer group adoption variables to zero for each observation and then estimating predicted probabilities.

The left panel of figure 3 shows the fitted cumulative adoption curve plotted against the true adoption curve. The fitted curve closely tracks the true adoption curve for all years. The center panel of figure 3 shows the counterfactual of no peer effects plotted against the true adoption curve. As expected, the counterfactual with no peer effects under-predicts LEPA adoption in every period. The right panel of figure 3 shows the difference between the predicted and counterfactual adoption curve. Omitting peer effects results in an under-estimation of true annual LEPA adoption by at least 1,000 units each year between 2001 and 2014. This corresponds to underestimating true adoption by approximately 10-12 percent in each of these years.

The amount of actual water savings associated with converting from conventional center pivot to LEPA remains an empirical question. Some studies conclude that more efficient irrigation technologies are essential to solving the world's water problems (e.g. Jury and Vaux, 2005, Evans and Sadler, 2008). Economists, however, have argued that behavioral adjustments associated with technological change may lessen or even outweigh any potential water savings. For example, using data from Kansas, Pfeiffer and Lin (2014a) and Li and Zhao (2018) find a rebound effect after adopting LEPA. The rebound occurs because irrigation becomes effectively less costly and farmers have incentives to irrigate more acres, grow more water-intensive crops, or both. It is therefore plausible that peer effects in the adoption of LEPA in Kansas have actually exacerbated rather than slowed depletion of the High Plains Aquifer.

7. Conclusion

In this paper, we analyze detailed irrigation behavior data at the water right level and find strong evidence for peer effects in the adoption of LEPA technology in the High Plains Aquifer region of Kansas net of environmental factors. By using spatial bands around each water right as a peer group measure, we uncover an intuitive pattern of spatial peer effects that diminish over space. Our results indicate that one more LEPA installation within 1 km increases the probability of LEPA adoption by 0.2 percentage points, on average. For LEPA installations that are 2-5 km away, the average marginal effect on LEPA adoption is 0.05 percentage points on average. We also find that the likelihood of adopting LEPA increases for growers cultivating water intensive crops such as corn and for large irrigated acreages. Energy prices also play a major role in adoption of LEPA.

We find little evidence that long-run trends in temperature and precipitation or short-run fluctuations in heat stress affect LEPA adoption.

Using our model estimates, we simulate a counterfactual LEPA adoption curve in the absence of any peer effect to illustrate policy implications. We find that cumulative LEPA adoptions would have been about 10-12 percent lower in most years in the absence of any intra-grower peer influence. This result corresponds to about 1,000-1,700 fewer LEPA installations per year over the final 14 years of our analysis (2001-2014). In light of these results, increasing the recognition and salience of water saving irrigation adoptions would be expected to increase the rate of adoption. Additionally, expenditures on cost share programs and provision of government or university extension services may be more effective if they can complement spatial dispersion of grower peer networks.

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Tables

Table 1. Summary statistics for model variables.

Variable (units)	Definition	Mean	Std.D	Min	Max
Peer adopters, 0-1 km	Number of water rights have LEPA installed	0.6	0.9	0	9
Peer adopters, 1-2 km	Number of water rights have LEPA installed	2.2	2.3	0	17
Peer adopters, 2-5 km	Number of water rights have LEPA installed	14.4	12.5	0	71
Total neighbors	Total water rights within 5 km	35.2	16.7	1	99
Slope (%)	Soil slope	2.0	2.6	0.0	19.0
Elevation (meters)	Distance above sea level	848.6	253.0	294.3	1,631.0
Acidic soils	Soil pH level less than 6.0, binary 0,1	0.01	0.1	0.0	1.0
Basic soils	Soil pH level greater than 7.5, binary 0,1	0.7	0.4	0.0	1.0
Soil Organic Carbon (g/m^2)	Total organic carbon in soil	8,366.1	3,272.7	959.0	23,149.6
Root Zone Available Water Storage (mm)	Volume of plant available storage in root zone	254.6	50.8	39.1	335.0
Drought Soil Landscape	Drought vulnerable soils, binary 0,1	0.1	0.2	0.0	1.0
Specific Yield	Aquifer yield ratio	16.6	3.5	5.0	25.0
Hydraulic Conductivity (ft/day)	Ease with which water moves through aquifer	280.5	93.3	49.4	476.3
Depth to Water (feet)	Distance from surface to top of water table	118.8	80.1	0.0	365.4
Recharge (inches/year)	Average annual recharge for 2000-2009	2.2	2.4	0.0	14.1
Energy Price ($/mmbtu)	County-specific cost of energy	10.7	5.0	5.7	28.2
Authorized Quantity (acre feet)	Maximum authorized use per the water right	290.0	211.5	0.0	3,596.0
Authorized Rate (gallons/minute)	Maximum authorized pump rate per the water right	901.4	451.9	0.0	5,875.0
Seniority	Age of the water right	29.2	10.1	3.0	72.0
Total Acres Irrigated (acres)	Total acres irrigated during the year	145.2	123.4	0.0	3,900.0
Hours Pumped (hundreds of hours)	Total hours pumped during the year	6.2	11.4	0.0	326.4
Cost Share Payments ($/water right)	Annual county-level cost share payments	36.0	142.4	0.0	1,800.2
Degree days between 8 and 32C (degrees*days)	Ten year moving average of annual count of time spent greater than 8C and less than 32C	2,025.2	126.5	1,703.4	2,333.4

Average degree days over 32C (degrees*days)	Ten year moving average of annual count of time spent greater than 32C	39.0	8.4	16.0	64.8
Degree days over 32C (degrees*days)	Annual count of time spent greater than 32C	41.9	22.1	2.6	150.8
Precipitation (mm)	Ten year moving average of annual rainfall	410.6	72.5	253.6	648.0
Intensive Crop Dummy	Dummy for water intensive crop last year	0.2	0.5	0.0	1.0
Center Pivot Dummy	Dummy for center pivot technology last year	0.3	0.4	0.0	1.0

The summary statistics are based on a panel of 18,486 water right identifications over 25 years (1990-2014), resulting in a sample size of 449,353.

Table 2. Odds ratios for primary specifications for the 0-1 km, 1-2 km, and 2-5km peer group.

	(1)	(2)	(3)	(4)
Lagged no. adopters 1 km	1.041***	1.040***	1.033**	1.028**
	(0.014)	(0.014)	(0.014)	(0.014)
Lagged no. adopters 1-2 km	1.037***	1.036***	1.030***	1.028***
	(0.007)	(0.007)	(0.007)	(0.007)
Lagged no. adopters 2-5 km	1.017***	1.016***	1.010***	1.007***
	(0.002)	(0.002)	(0.002)	(0.002)
County energy price	1.010**	1.012***	1.050***	1.008
	(0.004)	(0.004)	(0.007)	(0.009)
Depth to water interacted with county energy price	1.0001***	1.0001***	1.0001**	1.0002***
	(2.85E-05)	(2.74E-05)	(3.36E-05)	(4.30E-05)
Total no. neighbors	0.991***	0.991***	0.995***	0.996***
	(8.39E-04)	(8.23E-04)	(9.36E-04)	(9.43E-04)
Authorized quantity	1.000	1.000	1.0001*	1.0001*
	(6.41E-05)	(6.40E-05)	(6.58E-05)	(6.60E-05)
Authorized rate	1.0001***	1.0001***	1.0001**	1.0001**
	(2.74E-05)	(2.75E-05)	(2.83E-05)	(2.82E-05)
Seniority	1.019***	1.019***	1.018***	1.017***
	(0.001)	(0.001)	(0.001)	(0.001)
Lagged acres irrigated	1.001***	1.001***	1.001***	1.001***
	(7.59E-05)	(7.59E-05)	(7.74E-05)	(7.74E-05)
Lagged hours pumped	1.003***	1.003***	1.004***	1.004***
	(9.20E-04)	(9.16E-04)	(9.45E-04)	(9.56E-04)
Center pivot dummy	1.986***	1.974***	1.903***	1.927***
	(0.045)	(0.045)	(0.044)	(0.045)
Lagged water intensive crop	1.258***	1.257***	1.277***	1.280***
	(0.026)	(0.026)	(0.027)	(0.027)
County EQIP subsidy	1.000	1.0002**	1.0003***	1.000
	(8.09E-05)	(8.14E-05)	(8.40E-05)	(9.80E-05)
Slope	0.986***	0.988**	0.987**	0.989**
	(0.005)	(0.005)	(0.005)	(0.005)
Elevation	1.000	1.000	1.0001*	1.000
	(6.26E-05)	(6.27E-05)	(7.23E-05)	(7.22E-05)
Acidic soils	1.209	1.189	0.968	1.023
	(0.157)	(0.154)	(0.130)	(0.141)
Basic soils	0.923**	0.936	0.932	0.916**
	(0.038)	(0.038)	(0.041)	(0.040)
Soil organic carbon	0.999***	0.999*	0.999***	0.999***
	(4.60E-06)	(4.56E-06)	(5.42E-06)	(5.44E-06)

Root zone available water storage	0.999***	0.999***	0.999*	0.999*
	(4.32E-04)	(4.36E-04)	(4.69E-04)	(4.69E-04)
Drought soil landscape	0.939	0.957	1.021	0.989
	(0.070)	(0.072)	(0.080)	(0.078)
Specific yield	0.999	0.997	0.990**	0.990***
	(0.004)	(0.004)	(0.004)	(0.004)
Hydraulic conductivity	1.000	1.000	1.000	1.000
	(1.42E-04)	(1.42E-04)	(1.57E-04)	(1.57E-04)
Depth to water	0.999**	0.999***	1.000	0.999**
	(3.52E-04)	(3.47E-04)	(4.39E-04)	(5.17E-04)
Aquifer recharge	1.008	1.005	1.006	1.007
	(0.005)	(0.005)	(0.005)	(0.005)
10 year avg. precip.	0.999*	0.999**	1.001	1.001
	(4.88E-04)	(4.63E-04)	(8.79E-04)	(0.001)
10 year avg. degree days over 32C	0.980***	0.972***	0.983*	1.045***
	(0.006)	(0.005)	(0.009)	(0.014)
Lagged degree days over 32C	1.001	1.002	1.002	1.000
	(0.001)	(0.001)	(0.001)	(0.003)
10 year avg. degree days 8C-32C	1.000	1.000	1.004***	1.002
	(3.87E-04)	(4.13E-04)	(0.001)	(0.002)
Spatial effects	GMD	Ag. District	County	County
Year FE	Yes	Yes	Yes	No
Ag. District X Year FE	No	No	No	Yes
R^2	0.11	0.11	0.12	0.12
Observations	193,085	193,085	193,037	192,785
Marginal effects				
1 km peer	0.00253***	0.00247***	0.00200**	0.00174**
	(8.70E-04)	(8.70E-04)	(8.69E-04)	(8.69E-04)
1-2 km peer	0.00225***	0.00224***	0.00184***	0.00174***
	(4.09E-04)	(4.08E-04)	(4.07E-04)	(4.08E-04)
2-5 km peer	0.00103***	0.00100***	0.000598***	0.000449***
	(1.06E-04)	(1.04E-04)	(1.10E-04)	(1.12E-04)
County energy price	0.00156***	0.00181***	0.00367***	0.00196***
	(2.11E-04)	(2.15E-04)	(3.34E-04)	(4.42E-04)

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3. Odds ratios for separate specifications of the 0-1 km, 1-2 km, and 2-5km peer group.

	(1)	(2)	(3)
Lagged no. adopters 1 km	1.048***	1.039***	
	(0.014)	(0.006)	
Lagged no. adopters 1-2 km			
Lagged no. adopters 2-5 km			1.010***
			(0.002)
County energy price	1.008	1.008	1.009
	(0.009)	(0.009)	(0.009)
Depth to water interacted with county energy price	1.0002***	1.0002***	1.0002***
	(4.29E-05)	(4.29E-05)	(4.31E-05)
Total no. neighbors	0.999	0.998***	0.996***
	(7.65E-04)	(8.11E-04)	(9.26E-04)
Authorized quantity	1.0001*	1.0001*	1.0001*
	(6.59E-05)	(6.60E-05)	(6.60E-05)
Authorized rate	1.0001**	1.0001**	1.0001**
	(2.83E-05)	(2.82E-05)	(2.82E-05)
Seniority	1.017***	1.017***	1.017***
	(0.001)	(0.001)	(0.001)
Lagged acres irrigated	1.001***	1.001***	1.001***
	(7.74E-05)	(7.74E-05)	(7.73E-05)
Lagged hours pumped	1.004***	1.004***	1.004***
	(9.57E-04)	(9.57E-04)	(9.55E-04)
Center pivot dummy	1.941***	1.935***	1.932***
	(0.045)	(0.045)	(0.045)
Lagged water intensive crop	1.282***	1.280***	1.281***
	(0.027)	(0.027)	(0.027)
County EQIP subsidy	1.000	1.000	1.000
	(9.75E-05)	(9.77E-05)	(9.78E-05)
Slope	0.989**	0.989**	0.987**
	(0.005)	(0.005)	(0.005)
Elevation	1.0001*	1.0001*	1.0001*
	(7.22E-05)	(7.22E-05)	(7.23E-05)
Acidic soils	1.036	1.021	1.035
	(0.142)	(0.140)	(0.143)
Basic soils	0.897**	0.906**	0.914**
	(0.039)	(0.040)	(0.040)
Soil organic carbon	0.999***	0.999***	0.999***
	(5.43E-06)	(5.43E-06)	(5.44E-06)

Root zone available water storage	0.999*	0.999*	0.999*
	(0.000)	(4.69E-04)	(4.69E-04)
Drought soil landscape	0.972	0.977	0.983
	(0.077)	(0.077)	(0.078)
Specific yield	0.989***	0.990***	0.989***
	(0.004)	(0.004)	(0.004)
Hydraulic conductivity	1.000	1.000	1.000
	(1.56E-04)	(1.56E-04)	(1.56E-04)
Depth to water	0.999**	0.999**	0.999**
	(5.17E-04)	(5.16E-04)	(5.18E-04)
Aquifer recharge	1.008	1.007	1.008*
	(0.005)	(0.005)	(0.005)
10 year avg. precip.	1.001	1.001	1.001
	(0.001)	(0.001)	(0.001)
10 year avg. degree days over 32C	1.047***	1.047***	1.045***
	(0.014)	(0.014)	(0.014)
Lagged degree days over 32C	1.000	1.000	1.000
	(0.003)	(0.003)	(0.003)
10 year avg. degree days 8C-32C	1.002	1.002	1.002
	(0.002)	(0.002)	(0.002)
Spatial effects	County	County	County
Year FE	No	No	No
Ag. District X Year FE	Yes	Yes	Yes
R^2	0.12	0.12	0.12
Observations	192,785	192,785	192,785
Marginal effects			
Peer effect	0.00290***	0.00237***	0.000606***
	(8.43E-04)	(3.82E-04)	(1.07E-04)
County energy price	0.00206***	0.00205***	0.00198***
	(4.42E-04)	(4.42E-04)	(4.43E-04)

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Linear probability model estimates.

	(1)	(2)	(3)	(4)
Lagged no. adopters 1 km	0.00215*	0.00212*	0.00252*	0.00403**
	(0.001)	(0.001)	(0.002)	(0.002)
Lagged no. adopters 1-2 km	0.00265***	0.00236***	0.00379***	0.00412***
	(5.71E-04)	(5.47E-04)	(8.39E-04)	(8.37E-04)
Lagged no. adopters 2-5 km	0.00108***	0.000762***	0.00164***	0.00135***
	(1.37E-04)	(1.44E-04)	(1.94E-04)	(2.08E-04)
County energy price	-0.00118***	1.39E-02	5.11E-04	-0.121
	(2.79E-04)	(7.480)	(5.63E-04)	(0.355)
Depth to water interacted with county energy price	1.65e-05***	2.05e-05***	6.73e-06*	1.98e-05***
	(1.81E-06)	(3.20E-06)	(3.72E-06)	(6.37E-06)
Total no. neighbors	-0.000468***	-0.000311***		
	(4.37E-05)	(4.66E-05)		
Authorized quantity	3.74E-06	4.07E-06		
	(4.22E-06)	(3.90E-06)		
Authorized rate	5.44e-06***	4.63e-06***		
	(1.83E-06)	(1.72E-06)		
Seniority	0.00120***	0.000961***		
	(8.08E-05)	(7.50E-05)		
Lagged acres irrigated	6.54e-05***	6.31e-05***	8.86e-05***	8.24e-05***
	(7.20E-06)	(6.94E-06)	(1.19E-05)	(1.18E-05)
Lagged hours pumped	6.15E-05	8.57E-05	-0.000354***	-0.000402**
	(5.66E-05)	(5.61E-05)	(7.68E-05)	(7.68E-05)
Center pivot dummy	0.0425***	0.0384***	0.0248***	0.0265***
	(0.001)	(0.001)	(0.003)	(0.003)
Lagged water intensive crop	0.0163***	0.0173***	0.0158***	0.0162***
	(0.002)	(0.001)	(0.002)	(0.002)
County EQIP subsidy	-9.91E-06	-1.21E-04	-2.34e-05***	0.000429*
	(6.99E-06)	(0.078)	(7.01E-06)	(2.36E-04)
Slope	-0.000739**	-0.000605*		
	(3.55E-04)	(3.66E-04)		
Elevation	-4.25E-07	7.18E-06		
	(4.25E-06)	(4.73E-06)		
Acidic soils	0.0172**	3.14E-03		
	(0.009)	(0.009)		
Basic soils	-0.00552**	-0.00446		
	(0.003)	(0.003)		
Soil organic carbon	-3.37E-07	-1.08e-06***		
	(2.84E-07)	(3.27E-07)		

Root zone available water storage	-6.17e-05**	-2.99E-05		
	(2.84E-05)	(2.86E-05)		
Drought soil landscape	-2.66E-03	3.36E-04		
	(0.005)	(0.005)		
Specific yield	-7.66E-05	-0.000555**		
	(2.35E-04)	(2.44E-04)		
Hydraulic conductivity	-6.57E-06	-7.04E-06		
	(9.34E-06)	(9.77E-06)		
Depth to water	-0.000132***	-0.000140***	0.0107***	0.00806***
	(2.03E-05)	(3.26E-05)	(8.72E-04)	(0.002)
Aquifer recharge	2.51E-04	3.60E-04		
	(2.96E-04)	(2.91E-04)		
10 year avg. precip.	-6.86e-05*	-0.000115	-0.000562***	-0.00583***
	(3.71E-05)	(0.367)	(8.35E-05)	(0.001)
10 year avg. degree days over 32C	-2.22E-04	-3.02E-03	0.00293***	0.0896**
	(4.20E-04)	(1.844)	(9.18E-04)	(0.040)
Lagged degree days over 32C	3.62E-05	1.85E-03	-0.000549***	3.36E-03
	(1.76E-04)	(0.003)	(1.73E-04)	(0.003)
10 year avg. degree days 8C-32C	-7.39e-05***	-2.61E-05	1.99E-04	-0.0005
	(2.85E-05)	(0.093)	(1.25E-04)	(0.001)
Water right FE	No	No	Yes	Yes
Water right RE	Yes	Yes	No	No
Ag. District X Year FE	Yes	No	Yes	No
County X Year FE	No	Yes	No	Yes
R^2	0.10	0.11	0.12	0.14
Observations	193,085	193,085	193,085	193,085

*** p<0.01, ** p<0.05, * p<0.1

Figures

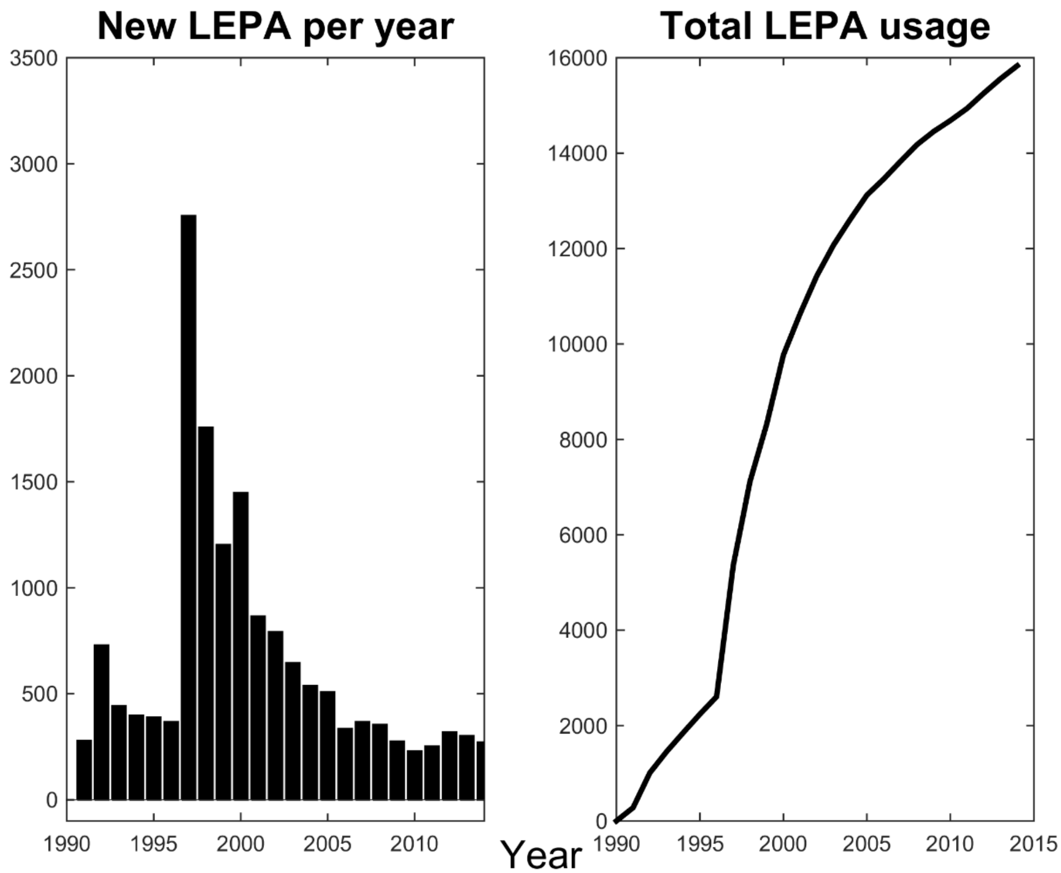

Figure 1. New LEPA per year (left) and cumulative usage over time (right).

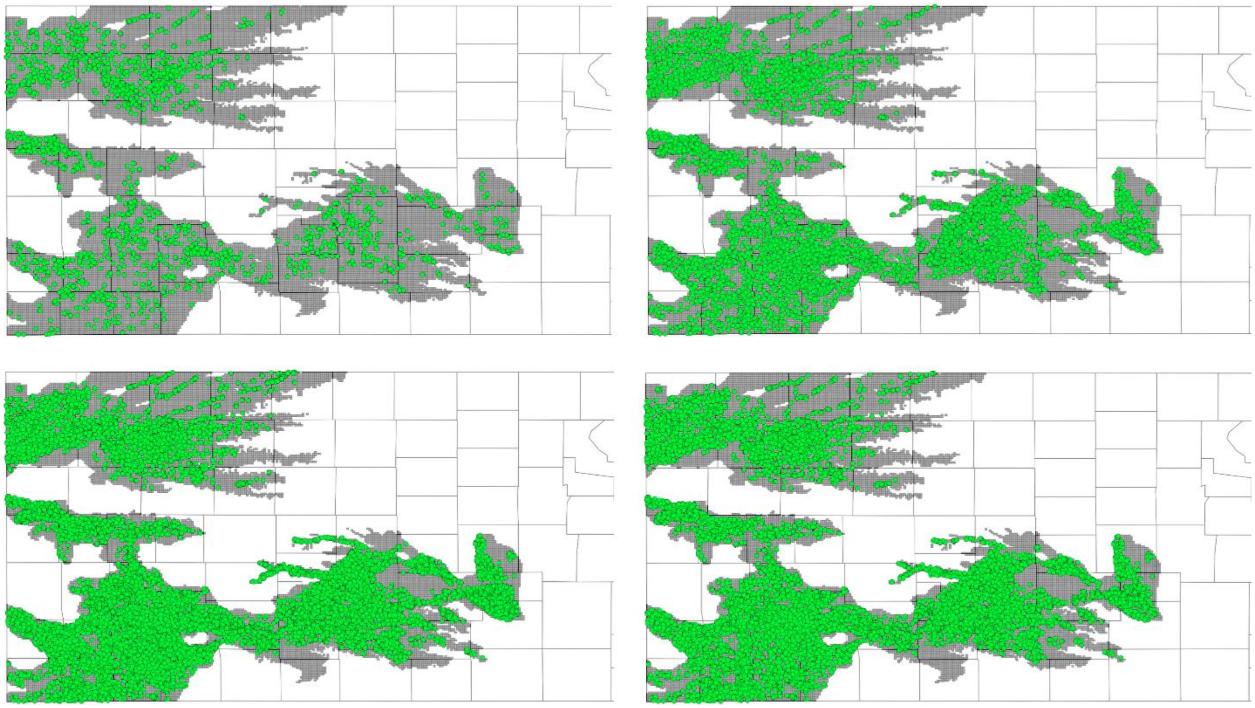

Figure 2. Spatial pattern of LEPA use in the Kansas High Plains Aquifer. Clockwise from top-left: 1995, 1998, 2002, 2010.

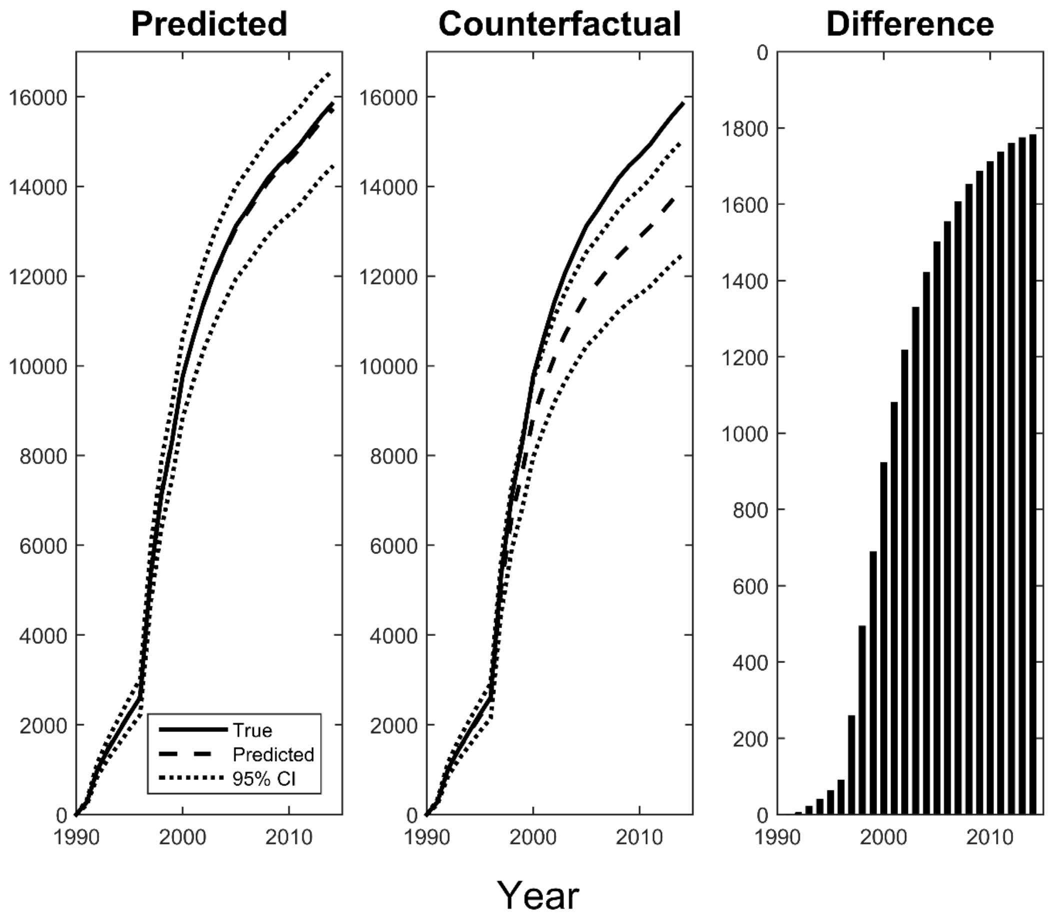

Figure 3. Fitted cumulative LEPA adoption curve (left), counterfactual with no peer effects (middle), and per-period difference between the fitted and counterfactual (right).

Additional Figures

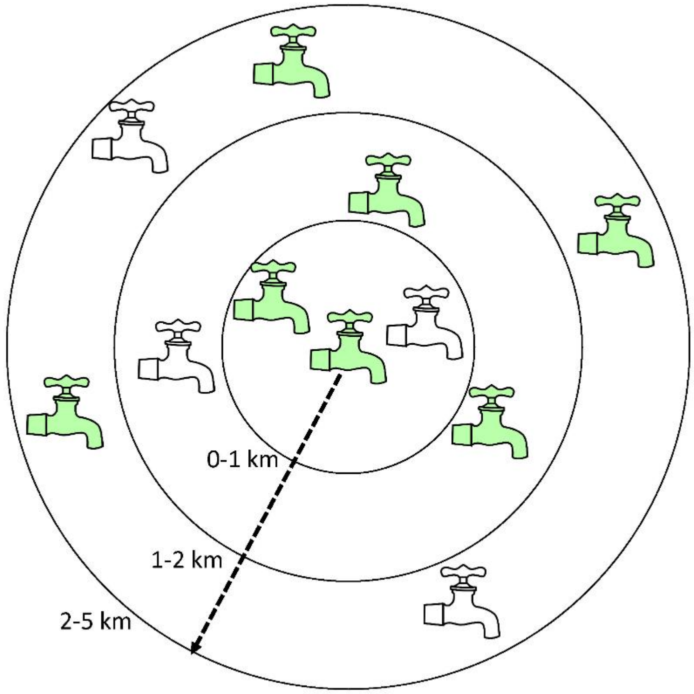

Figure A1. Sample 0-1 km, 1-2 km, and 2-5 km buffers about a water right.
Note: green indicates LEPA adoption and white is non-LEPA. In this example, the focal water right has one LEPA peer in the 0-1 km buffer, two LEPA peers in the 1-2 km buffer, and three LEPA peers in the 2-5 km buffer.