The Role of Peer Effects in Resource Extraction – The Case of Kansas Groundwater

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Abstract

Social interaction and peer effects are recognized as a potentially important factor in the diffusion of new technologies. Peer effects have policy relevance, as they can expedite adoption of socially desirable technologies. In this paper, we investigate the role of peer effects in the adoption of groundwater rights for agricultural irrigation in Kansas. Using detailed data on groundwater rights and a definition of the peer group as the 13 nearest neighbors, we find that an additional groundwater adopter within the peer group increases the relative odds of adoption by 9 percent. The effect of peers is found to diminish with distance. Our results provide evidence of potentially large gains to policy makers in accounting for peer effects and social multipliers when designing resource conservation programs.

Introduction

Adoption of new technologies is often cited as being critical to reducing the use of scarce inputs while meeting growing demand for food and resource commodities. Understanding the factors that influence these adoption decisions is important for both normative and positive objectives. In the positive sense, knowing the determinants of adoption can help in predicting adoption patterns (e.g. which firms are likely to adopt first). In the normative sense, understanding why some individuals or firms adopt faster than others can help in encouraging particular patterns of adoption of socially desirable technologies (e.g. vaccinations). Frequently, an individual or firm has incomplete knowledge about a technology prior to adoption. Thus, some investment in learning about the new technology is coupled with adoption. If there are multiple adopters facing similar circumstances, then the process of technology experimentation and learning may be social. Consequently, potential adopters may learn the process of using the new technology or the benefits of using the new technology from previous adopters (Foster and Rosenzweig, 1995, Brock and Durlauf, 2010, Conley and Udry, 2010, Bollinger and Gillingham, 2012, Oster and Thornton, 2012, Felthoven, Lee, et al., 2014). Indeed, experimentation at the firm or individual level has been shown to generate learning spillovers within peer networks, leading to suboptimal rates of adoption (Foster and Rosenzweig, 1995, Oster and Thornton, 2012).

In this paper, we examine the role of peer effects in the spatial-temporal adoption of groundwater rights for agricultural irrigation in Kansas. Irrigation has long been recognized as critical to agricultural production in the western United States, where precipitation alone is often insufficient to meet evapotranspiration requirements of crops. For instance, average annual precipitation in western Kansas ranges from 16 to 22 inches while the seasonal water requirement for corn is upwards of 23 inches (Schneekloth and Andales, 2017). Large rates of pumping over the last few decades have raised concerns over the sustainability of irrigation from groundwater in many important agricultural areas of the US such as the High Plains and California's Central Valley (Scanlon, Faunt, et al., 2012, Steward, Bruss, et al., 2013). Some portions of the High Plains aquifer are projected to have a useable lifespan of fewer than 25 years (Buchanan, Wilson, et al., 2015). Increased reliance on groundwater for water and food security is probable as more frequent and intense climate extremes increase variability in precipitation and surface water (Taylor, Scanlon, et al., 2013).

Prior to World War II, irrigation from groundwater was largely limited by technological constraints associated with lifting and applying water from aquifers. Beginning with the post-World War II era, the combined availability of center pivot technologies and automobile engines, which could be adapted to power groundwater pumps, reduced the costs of pumping and applying large volumes of water. With the enactment of the Kansas Water Appropriation Act of 1945 (KWAA), any person seeking a right to use water for agricultural production in Kansas must apply for and obtain a permit. The pattern of groundwater rights adoption for irrigation over time has followed the well-known S-curve of technology diffusion noted by Griliches (1957) (Fig. 1). There has also been a pronounced spatial pattern in adoption: newly obtained groundwater irrigation developments have been more likely to occur where groundwater irrigation has already been acquired (Fig. 2).

In the context of Kansas groundwater, the presence of peer effects means the returns for an individual adopting irrigation changes in response to the adoption decisions of his or her peers. For example, growers likely differed in their knowledge about groundwater exploitation and the costs and benefits of groundwater irrigation. As more knowledgeable growers adopted groundwater irrigation, nearby dryland farmers learned about the benefits of increased production yields, drought protection, and climate adaptation (Thorfinnson and Epp, 1953, Foster and Rosenzweig, 1995). If peer effects do in fact drive adoption of groundwater exploitation, then policy makers can potentially steer adoption of water-saving irrigation technologies where they are most efficient (Müller and Rode, 2013, Graziano and Gillingham, 2015, Rode and Weber, 2016). Moreover, peer effects have important policy consequences in a variety of other natural resource contexts, including oil (Lin, 2009), forests (Robalino and Pfaff, 2012), and fisheries (Felthoven, et al., 2014, Lynham, 2017).

Identification of peer effects in technology adoption is made difficult by the problem of correlated unobservables, self-selection of peers, and simultaneity (Manski, 1993, Soetevent, 2006). For instance, when two neighbors adopt a new technology, how does the econometrician separately identify learning from common environmental influences? Likewise, if individuals with similar preferences move to the same geographic areas, then common preferences might be mistaken for peer effects. Finally, an individual's peer group affects that individual's decisions, just as the individual's decision affects their peer group.

We exploit spatial and temporal variation in rights to appropriate groundwater for irrigation in order to separately identify peer effects from other contextual, self-selection, and simultaneity factors in the adoption of irrigation over time. More specifically, we estimate how the relative odds of developing groundwater for irrigation changes depending on the number of previous irrigation adopters within a grower's peer network. We define a grower's peer network at two different levels: (i) the nearest 13 neighbors by distance and (ii) the nearest 25 neighbors by distance. To control for the possibility of peer self-selection and socioeconomic factors, we include a rich set of school district (SD) and groundwater management district (GMD) fixed effects. The 13 and 25 nearest neighbor peer group definition is consistent with Towe and Lawley (2013) and avoids any potential problems of measurement bias against growers on the edge of pre-defined district boundaries (Fotheringham and Wong, 1991, Graziano and Gillingham, 2015) and spurious correlations caused by differing grower densities across districts (Towe and Lawley, 2013). Statewide and groundwater management district-specific time trends are included to control for time-varying correlated unobservables (e.g. macro-level and localized adoption trends unrelated to peer learning). Finally, simultaneity is not a concern because our measure of peer effects is the number of previously adopted water rights (Bollinger and Gillingham, 2012). We also test the effects of a rich set of climate, hydrology, and soils data, which are spatially merged to irrigation adoption data.

A unique aspect of our research is rich spatially and temporally varying data on irrigation adoption. Importantly, the independent variable of interest, cumulative number of peer adopters up to year t, changes over time and allows us to identify the role of peer effects. Location-specific data on the adoption of irrigation over a 72-year period (1943-2015) are obtained from the Water Information Management and Analysis System (WIMAS) maintained by the Kansas Division of Water Resources. We measure the adoption of irrigation as the date the water right was obtained, which corresponds closely with the date of initiating irrigation because water right holders lose their right if not put to beneficial use within a short period of time.

Overall, we find strong evidence that peer effects influence the decision to adopt rights to groundwater exploitation. At the peer group definition of 25 nearest neighbors, a one-unit increase in the stock of adopters in the previous calendar year is conservatively estimated to increase the odds of adoption by approximately 5 percent. At the 13 nearest neighbor peer group, a one-unit increase in the stock of adopters in the previous year is estimated to increase the odds of adoption by 9 percent. These results are statistically significant and robust to substantial sensitivity analysis. Our results suggest resource extraction propagates to some extent through social interaction. This finding provides evidence of large gains to resource managers in accounting for peer effects and social multipliers when designing conservation programs. We find weak evidence of climatic trends affecting the odds of groundwater adoption.

The remainder of this paper is as follows. Section I provides background on water rights in Kansas. Section II provides conceptualization of the challenges and opportunities for identifying peer effects. Section III presents the empirical approach. Section IV describes the data. Results are presented in Section V. The paper concludes with a discussion of our finding and policy implications.

Background on water rights in Kansas

Surface water availability is limited in most of western and central Kansas and represented an early obstacle to production agriculture in the state.[1] Where surface water was lacking, farmers could tap groundwater in limited fashion using windmill-powered pumps. However, windmill-powered pumps generally lacked the ability to lift large volumes of water and thus were not a viable means of large scale irrigation. Of the 37,000 total acres in irrigation in Kansas in 1909, only 5% was irrigated from groundwater. By 1920, the proportion of irrigated acres sourced from groundwater increased to nearly 30% (Bureau of the Census of Department of Commerce, 1922), an increase largely owing to the advent of internal combustion engines.

In Kansas there has existed reasonably clear water law establishing rights to groundwater since becoming a state in 1861. At the time, common law provided the absolute ownership doctrine for groundwater, meaning land owners possessed complete ownership of the groundwater under the land. Following a 1944 Governor's Task Force Report investigating Kansas' use of riparian and absolute ownership doctrines, Kansas Legislature

[1] An exception is the Arkansas River, which was diverted in the late 19th century to serve Gray and Ford counties in southwest Kansas.

adopted the Kansas Water Appropriation Act of 1945 (KWAA). Amongst the changes made by KWAA was the requirement that any person seeking a right to use water for agricultural production had to apply to the Division of Water Resources for a permit.[2] Once a permit is obtained, the permit holder has a specific window of time to construct a well. If the well is constructed within the allowed window of time, the permit holder must "perfect" the groundwater appropriation by putting the water to beneficial use. Water rights are limited in maximum annual quantities of water, instantaneous diversion rates, and place of use. Moreover, water rights can be lost if they are not exercised without valid reason for a specific period of successive year (usually four or five) (K.S.A. 82a-718a).

Groundwater development in Kansas grew quickly subsequent to KWAA, owing to the combined availability of automobile engines to power groundwater pumps and center pivot technologies to apply large volumes of water (Fig. 1). From 1944 to 1970 the number of new rights to appropriate groundwater increased from less than 1,000 to over 11,000. Approximately 33,000 rights have been developed since passage of KWAA and the pattern has followed the well-known s-curve noted by Griliches (1957) (Fig. 1). There has also been a pronounced spatial pattern: newly obtained water rights have been more likely to occur where water rights have already been acquired (Fig. 2). In particular, much of the groundwater development has taken place in western and southcentral Kansas overlaying the Ogallala Aquifer (Fig. 2 and 3).

Typical annual reported irrigation in Kansas is approximately 3.5 million acre-feet applied to 3 million irrigated acres (Lanning-Rush, 2016). These annual withdrawals greatly

[2] Rights to groundwater use held under absolute ownership doctrine prior to KWAA were recognized as vested rights.

exceeds the Ogallala's rate of recharge in Kansas (0.75 million acre-feet) (Buchanan, et al., 2015). Consequently, water tables have declined, with declines up to 150 feet in southwestern Kansas. Secure water availability is a significant concern for Kansas agriculture, a state that consistently ranks in the top 10 nationally in wheat, grain sorghum, and grain corn production as well as total acres in cropland (Kansas Department of Agriculture, 2015). Recognizing problems of overdraft of the Ogallala Aquifer, the 1972 Kansas Legislature passed legislation (i.e. the GMD Act) which would later enable groundwater management districts to manage aquifer exploitation at local levels. Following the GMD Act, five groundwater management districts were established in western and central Kansas. Based on recommendations of these management districts, the chief engineer of the Division of Water Resources promulgated various regulations designed to extend the life of the Ogallala, including regulations on minimum well spacing, requirements for metering, prohibitions against water waste, and development of safe yield and depletion formulas.

Identifying Peer Effects

The key issue identified by the existing literature on peer effects is that the clustering of outcomes at a spatial or group level can stem from two different types of effects (Manski, 1993, Cohen-Cole and Fletcher, 2008). The first type of effects are exogenous or *contextual* effects. These are influences or characteristics that, by virtue of being commonly shared by individuals within some defined group, generate similar or correlated behavior. Examples in the context of our problem include similar soil characteristics, hydrology characteristics, and climate. The second type of effects are *endogenous* effects. These encompass interactions in which the behavior of an individual is causally impacted by the behavior of other individuals within his group. The channel through which that individual's behavior is impacted may be informational or real. A farmer in southwestern Kansas, for example, may observe or learn of the success of a neighbor that irrigated (i.e. well production and lithology) and subsequently decide to acquire a water right. In this paper, we are concerned with endogenous effects, or what have so far been referred to as peer effects.[3]

Several challenges arise in disentangling endogenous peer effects from contextual effects. One issue is the so-called "reflection problem" (Manski, 1993), which refers to the situation in which, within a given time frame, the decision of an individual impacts the decision of his group and vice versa. In our context, this problem is of little significance as the influence of an individual's decision to acquire a water right is likely to only be felt through a lag. As such, we follow the recent literature and assume that an agent's adoption decision may depend on the "installed base" of adoption decisions within his group. The installed base is simply the cumulative number of adoptions up to the previous time period (Bollinger and Gillingham, 2012).

Perhaps the most significant hurdle to identifying peer effects is to sufficiently control for the various contextual factors. While we include a relatively large set of covariates that plausibly impact the return to irrigation, there likely remain other unobserved factors that lead to a spatial clustering of adoption decisions. Thus, we also include fixed effects, trends, and GMD-specific common correlated effects (Pesaran, 2006). The latter are particularly

[3] The main reason it is important to identify whether an observed correlation is due to contextual or endogenous effects lies in their predictive differences. Consider, for example, if the spatial clustering of water rights were only due to contextual interactions. Then the impact of a regional-specific policy or weather shock would be confined to that region; there would be no spillover effects in the absence of an endogenous component.

important as Figure 3 demonstrates significant clustering at the GMD level. By including common correlated effects at this level we are able to capture non-linear GMD-specific fluctuations in adoption patterns.

Finally, there is also the challenge of how to define a peer group. In spatial contexts, one approach is to use an already defined boundary such as a county or school district. However, this type of definition tends to overstate an individual's group size and suffers from measurement error (individuals near the boundaries are not assigned as neighbors when they should be) (Graziano and Gillingham, 2015). Following Towe and Lawley (2013), we consider two different peer group definitions: (i) the 13 nearest neighbors and (ii) the 25 nearest neighbors.[4] This type of definition does not suffer from the boundary problem and by using two different group sizes, we are able test for whether the impact of one's peers dissipates with distance.

Empirical Model

We model the decision to acquire a groundwater right in a binary discrete choice framework.[5] In particular, in each year, a decision-maker (potential adopter) chooses whether or not to obtain a groundwater right on the basis of profit maximization. The profit associated with a groundwater right for individual i in year t is written as

[4] Nonetheless, we do estimate adoption models in which an individual's group is defined as their school district or as those individuals within a 1.0 and 1.5 km radius. Results based on these definitions are provided in the Appendix.

[5] We alternatively considered a duration type approach. In this case, the dependent variable consists of the length of time it takes an individual to acquire a water right. We opted not to use a duration approach, as simulations suggested that these types of models regularly reject the presence of peer effects when they are present. This appears to result from the fact that, within a peer group, the installed base and the time until adoption must always covary in a positive direction.

$$\pi_{it} = \underbrace{\delta y_{i(t-1)} + \beta' x_{it} + \eta_{it}}_{v_{it}} + \varepsilon_{it}$$

where $y_{i(t-1)}$ is the installed base, x_{it} is a vector of observable covariates, η_{it} is a vector of fixed effects and location-specific time trends, and ε_{it} is an IID type I extreme value residual. Following standard convention, the profit associated with not acquiring a groundwater right is normalized to zero, and thus adoption occurs when $\pi_{it} > 0$. Let d_{it} denote an indicator variable that takes a value of one when $\pi_{it} > 0$. The probability that $d_{it} = 1$ is given by the familiar logit expression:

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

Based on these probabilities, estimation of the model parameters is carried out via maximum likelihood.

The installed based is defined as: $y_{i(t-1)} = \sum_{h \in g[i]} D_{h(t-1)}$, where $D_{h(t-1)} = 1$ if individual h in peer group $g[i]$ had acquired a groundwater right at or before year $(t-1)$ ($g[i]$ denotes the peer group to which i belongs). The vector x_{it} can be decomposed into three sub-vectors

$$x_{it} = x_{l[i]} + x_t + x_{l[i],t}$$

where $x_{l[i]}$ is a vector of time-invariant, location-specific controls ($l[i]$ denotes the location of choice-maker i), x_t is a vector of common, time-specific controls, and $x_{l[i],t}$ is a vector of location and time specific factors. The $x_{l[i]}$ include a rich set of soil and hydrology characteristics; the x_t include deflated corn and wheat prices; and the $x_{l[i],t}$ include climate and weather variables that potentially influence the profitability of irrigation. Further details on these variables are given in the Data section.

As noted, other potentially important unobserved factors are captured by various fixed effects and location specific trends, η_{it}. As with the x_{it}, these factors can be categorized as either time-invariant, time-specific, or time and location specific. To capture unobserved time-invariant factors we include either groundwater management district (GMD) dummies or school district (SD) dummies. The former capture commonly shared groundwater characteristics that likely drive the initial acquisition of a water right.[6] We also include SD effects to capture unobserved time-invariant heterogeneity at a finer level. To capture unobserved statewide effects, we include a linear trend in all specifications. In some specifications we also include GMD-specific linear trends. Finally, to capture non-linear temporal and locations specific shocks, we interact a statewide common correlated effect (CCE) with GMD dummies. The CCE is defined as $\sum_i d_{it} / I_t$, where I_t is the number of individuals at time t that have still not adopted. Ultimately, our baseline results consist of five different specifications, each differing by the type of fixed effects, trends, and correlated effects.

There are two important features in our data that warrant additional discussion. The first feature is that once we observe a decision-maker obtain a groundwater right, we never observe that individual revert to the status of not owning a water right. In principle, an

[6] GMDs are local units of government which provide water-use administration and planning subject to approval by the Chief Engineer of the Kansas Division of Water Resources. Five GMDs were formed between 1973 and 1976 following the 1972 Kansas Legislature. All districts correspond to major portions of the High Plains aquifer. Primary use of groundwater in the districts is for agricultural irrigation.

individual may relinquish their water right if it is not exercised for four or five consecutive years, but we do not observe this possibility. From a modeling standpoint, this presents the challenge of how to code the binary dependent variable in the years following the initial adoption event. One approach is to set $d_{it} = 1$ for all periods following the initial year of adoption. However, the problem with this approach is that it incorrectly assumes that the decision-maker actively renews the right each year. Alternatively, we could code all post-adoption decisions with a zero, as in Rode and Muller (2016). The problem with this approach is that an individual does not actually abstain from acquiring a right after they've obtained one. Our approach is to simply drop observations following the period a decision-maker acquires a groundwater right. As an example, if an individual acquired a water right in 1962, that individual would contribute 20 observations to the likelihood: 19 observations coded with a zero, and one observation coded with a one (recall that we observe the 72-year period (1943-2015)).

The question that naturally arises in taking this approach is how it impacts our peer effect estimate. To answer this question, we constructed a Monte Carlo simulation of technology adoption that is closely analogous to the problem herein. We simulated a diffusion process in which an individual actively chooses whether to adopt the technology, even after the initial adoption decision. We then estimated a model in which post initial adoption decisions were omitted. Further details and code regarding this simulation are provided in the appendix. In short, we found that omitting post initial adoption decisions produces a peer effect estimate that is below the true estimate. Thus, to the extent that individuals actively renew, or occasionally discontinue, their water right, our approach under-estimates the true peer effect.

The second feature that presents a challenge is that we do not observe individuals whom never acquire a groundwater right from 1943-2015. Here again, we explored the impact of this problem using simulation. We found that omitting individuals that never adopt from estimation does not bias the estimated peer effect coefficient.

Data

The data used for our estimation are drawn from multiple sources. Information about water rights identifications, points of diversion (i.e. wells), and priority dates are from the Water Information Management and Analysis System (WIMAS) maintained by the Kansas Division of Water Resources. For approximately 80% of the data, a single water right is associated with a single point of diversion. For water rights having multiple points of diversion (i.e. multiple wells), we determine a central location by calculating mean coordinates. In total, there are 33,518 unique water right identifications and 45,732 points of diversion.

Spatially explicit soils characteristics are obtained from SSURGO soil survey on the website of the USDA Natural Resource Conservation Service. These characteristics include detailed information on soil slope, elevation, available water capacity, soil erodibility, soil chemistry and soil physics, soil organic carbon, productivity indices for major commodities, root zone depth and water storage, soil texture, and drought vulnerability. Spatially explicit hydrology characteristics including predevelopment depth to water, saturated thickness, conductivity, and specific yield are obtained from The Kansas Geological Survey. Climate data are obtained from Schlenker and Roberts (2009). Prices received for corn and wheat, averaged at the annual level for the state of Kansas, are obtained from National Agricultural Statistics Service of the USDA and are adjusted to 2016 dollars using the Consumer Price

Index. Palmer Drought Severity Index (PDSI) for Kansas is retrieved from the National Oceanic and Atmospheric Administration's National Center for Environmental Information.

The well location and water right data obtained from WIMAS are matched by county to soil, hydrology, and weather data using spatial query functions in QGIS. Table 1 presents summary statistics of the variables used in model estimation.

Results

Tables 2-3 present our primary 13 and 25 nearest neighbor results, respectively. Standard errors are clustered at the SD level to account for model error correlation in all specifications. Column 1 presents results with GMD dummies to account for the fact that only certain regions of Kansas overlay major portions of the High Plains aquifer and there may be heterogeneity between these regions (Fig. 3). Column 2 adds GMD-specific time trends. Column 3 adds a CCE. In particular, column 3 includes a panel average of the dependent variable to account for unobserved fluctuations in adoptions unrelated to peer effects. The GMD-specific coefficient on CCE allows for differential responses to these fluctuations. Column 4 adds SD dummies to control for socioeconomic factors that may cluster at the district level. Geophysical variation within SDs is limited, so specifying school district fixed effects precludes estimation of the geophysical variables. Column 5 uses SD dummies but uses GMD-specific linear time trends instead of GMD dummies.

Looking across specifications, our results demonstrate robust evidence of peer effects in the adoption of groundwater. In Table 2, we present our primary results using the 13 nearest neighbor by distance definition of a peer group. Coefficients report odds ratios. The coefficient of most interest, stock of adopters in the previous calendar year (i.e. "installed base"), is positive and statistically and economically significant across all five specifications. This finding provides strong evidence that the cumulative number of adopters within a grower's closest geographic neighbors increases the odds that the grower will adopt groundwater rights. For example, in column 5, the coefficient on the lagged number of adopters indicates that one additional adopter within a grower's 13 nearest neighbors in the previous calendar year increases the odds of adoption by 10 percent on average. This point estimate is qualitatively unchanged by the inclusion of GMD effects and trends, CCE, and SD effects (e.g. columns 1-5 of Table 2).

In Table 3, we present our primary results using the 25 nearest neighbor definition of a peer group. Similar to the 13 nearest neighbor peer group definition, the coefficient on the lagged number of adopters, is positive, statistically and economically significant, and of similar magnitudes across all five specifications. This finding provides corroboration that the cumulative number of adopters within a grower's closest neighbors positively affects the odds that the grower will adopt ground water rights. For example, in column five, the coefficient on the lagged number of adopters indicates that one additional adopter within a grower's 25 nearest neighbors in the previous calendar year increases the odds of adoption by 6 percent on average. This point estimate is qualitatively unchanged across the five specifications (e.g. columns 1-5 of Table 3). Note also that the slightly smaller estimate for 25 nearest neighbor definition suggests that more distant neighbors have less of an effect on a potential adopter.

In Table 4, we present predictive margins for different numbers of previous adoptions within the peer group, holding all other covariates at their means. At the 13 nearest neighbor peer group definition, the probability of adoption is approximately 2 percent when there are zero previous adoptions within the peer group. With 12 previous adopters within the peer group, the probability of adoption increases to about 6 percent. At the 25 nearest neighbor peer group definition, the probability of adoption when there are zero previous adoptions is also about 2 percent. This probability increases to about 7 percent when the number of previous adopters increases to 24.

Our results also highlight the important role of the commodity price and geophysical and climate variables. Corn prices and wheat prices are positively and negatively associated with groundwater adoption, respectively. These results are highly statistically significant, robust to a variety of different controls, and are qualitatively similar across the three definitions of the peer group. The signs on these two commodity prices are intuitive, as corn is the most water intensive crop in Kansas, with approximately 35 percent or more of total harvested acres being irrigated. On the other hand, wheat is a predominantly dryland crop, with approximately 5 percent of total harvested acres being irrigated.

Model results in Tables 2-3 provide evidence of the impact of climate variables on the odds of adopting groundwater for irrigation. Reduced five-year average precipitation is associated with greater odds of adopting groundwater in the specifications in columns 1-2. However, this result is not robust to the CCE. Similarly, increased five-year averaged measures of degree days over 32 degrees Celsius is associated with greater odds of adopting groundwater. Again, this relationship is not robust to the CCE. Degree days between 8 and 32 degrees Celsius, which are widely recognized as favorable growing conditions, are positively associated with increased odds of adopting groundwater. The point estimate on this variable is statistically significant for four of the five specifications and is similar in magnitude across peer group definitions.

We report estimates of time-invariant hydrologic and soil characteristics in columns 1-3 and 7-9 of Tables 2-3. These variables are long-run averages and do not change over time. Additionally, geophysical variables are available for only a subset of the total water rights obtained from WIMAS. Greater predevelopment depth to water is found to negatively affect the odds of groundwater development, though the magnitude is small. This finding is consistent with irrigation costs increasing with pumping lift heights. Somewhat surprisingly, greater predevelopment saturated thickness and specific yield negatively affect the odds of groundwater development. This counterintuitive finding may result from the GMD fixed effects. Identification of the effects of predevelopment saturated thickness and specific yield comes from within-GMD variation, which is more limited than between-GMD variation (Buchanan, et al., 2015). Hydraulic conductivity, the ease with which water moves through porous media, is positive, statistically significant, and similar in magnitude across the different specifications and different peer group definitions. This is an interesting result in several ways. First, the relationship between hydraulic conductivity and groundwater adoption is intuitive because hydraulic conductivity determines the rate of groundwater movement into a production bore (e.g. water is more readily lifted). Second, drawdown at any given point in time is inversely proportional to hydraulic conductivity of the aquifer (e.g. transmission from surrounding water-bearing formations is "faster"). Lastly, because water is transmitted more easily across space when hydraulic conductivity is high, the gains from correcting common-pool extraction inefficiencies is highest (Edwards, 2016). Our results provide evidence that regions possessing aquifer characteristics that are beneficial to groundwater development are more likely to be adopted, but that this raises the possibility for inefficient spatial competition for groundwater over time.

The effect of slope is negative and statistically significant, a results which conforms to expectation as farms having high slope are likely to experience significant irrigation runoff. The coefficient on soil erodibility factor is negative but is only statistically significant for the specification in column 3. The sign of this coefficient is expected, as a greater erodibility factor implies greater soil losses from the erosive actions of water. The national commodity crop productivity index for corn and soybeans is positive but is not statistically significant. The coefficients on crop productivity indices for small grains and cotton are negative and statistically significant, which is consistent with these crops having a lower water requirement than irrigated corn.

Root zone depth is positive and significant at 5 percent or better across specifications and peer group definitions. Root zone available water storage is positive but only statistically significant for the specification in column 1. Greater root zone depth and available water storage allows more irrigation water to be stored in the root zone, which is then gradually used by the plants. If large amounts of plant-available water can be stored in root zones then irrigation schedules can be designed over longer intervals, effectively lowering the variable costs of irrigation. The total silt per unit soil is positive, a finding that is intuitive because silt textures will generally have good amounts of plant available water (e.g. compared to clay textures). The coefficient on bulk density is expected. Bulk density and organic matter are inversely related and lesser bulk density will more readily infiltrate water to plant root zones. Lastly, the drought vulnerability dummy is positive and highly significant. Thus, growers facing soil conditions which are vulnerable to drought have greater odds of adopting groundwater. Our finding in this regard is consistent with groundwater irrigation as a measure to adapt to conditions of water shortages.

To summarize, we find strong evidence of peer effects in the adoption of groundwater for irrigation. We also find strong evidence that commodity prices, and hydrologic and soil characteristics most related to water storage and plant availability influence adoption. We find mixed evidence of climatic conditions influencing the adoption of groundwater.

Additional Analyses and Robustness Checks

Spatial competition

While the previous literature has shown that hydraulic conductivity can lead to inefficient spatial competition over groundwater (Pfeiffer and Lin, 2012, Edwards, 2016), we hypothesize that the peer effect may intensify in regions where water moves rapidly across space. Table 5 demonstrates this intensifying effect of hydraulic conductivity as the number of adopters within the peer group increases. Column 1 reports estimates from the 13 nearest neighbor peer group and column 2 reports estimates from the 25 nearest neighbor peer group. Both peer group definitions are specified with GMD effects and trends and CCE.

Taken together, the results in columns 1 and 2 provide evidence that hydraulic conductivity influences the effects of previous peer group adopters on groundwater adoption. The results in columns 1 and 2 indicate that the effect of hydraulic conductivity on groundwater adoption is greater when there is a positive number of previous adopters within the peer group. Moreover, this effect is weakly increasing in the number of previous adopters. This finding is consistent with prevailing narratives of groundwater exploitation as spatial competition over a common pool resource (e.g. Pfeiffer and Lin, 2012, Edwards, 2016).

Matching water rights ownership

One potential concern in the spatial water rights data obtained from WIMAS is the possibility for one entity to hold multiple water rights. If a single entity serially adopts water rights within the same vicinity, then this could bias estimates of peer effects. We obtain the most recent correspondence list for water rights permits from the Kansas Division of Water Resources. This data provides names and addresses for 24,654 entities currently holding water rights. This is not the most ideal correspondence data, as there has been consolidation of water rights over time. However, insofar as water rights have been consolidated, this should result in a conservative estimate of ownership. This data reveal that approximately 45 percent of water rights holders have a single water right. Approximately 90 percent of water rights holders have five or fewer water rights.

We spatially match the correspondence data to the point of diversion data obtained from WIMAS. We then find the nearest 13 and 25 neighbors by distance, omitting neighboring water rights that list the same name and address as the focal water right. We estimate the same specifications as columns 3-5 of Tables 2 and 3. The results are entirely consistent with the results in Tables 2 and 3 and we therefore do not report them here.

Linear probability model and peer group definition

We perform several robustness checks on our primary results in Tables 2-3. Columns 1 and 2 of Table 6 show the results for the 13 and 25 nearest neighbor peer group estimated using a linear probability model (LPM) using year and water right fixed effects and CCE to control for idiosyncratic per-period shocks to adoption (the logit models did not converge with water right and year fixed effects). The LPM results are consistent with the logit results. The coefficients on the lagged number of adopters are positive and highly statistically significant for both peer group definitions. Comparison of the size of the coefficients between LPM and logit is not straightforward, however. With the LPM, there is a constant impact of the lagged number of adopters within the peer group on the dependent variable. In particular, an increase in the number of adopters in the previous year increases the probability of adopting groundwater by 1.5 percent and 0.9 percent for the 13 nearest neighbors and 25 nearest neighbors, respectively. No such straightforward statements are possible for the logit results in Tables 2-3 because the impact of any variable is nonlinear. Viewing the LPM results in relation to the predicted margins in Table 4 reveals that the logit produces more conservative marginal effects than the LPM. These results can be viewed as corroborating our previous results, which we view as preferable due to the logit model's better fitting nonlinearities for probabilities close to zero.

Columns 3-4 of Table 6 repeat column 3 of Tables 2 and 3 but define the peer group at the 1.0 and 1.5 km spatial buffer around the water right, respectively. By comparison, the average distance of a water right's 13 and 25 nearest neighbors is approximately 2.2 km and 2.9 km with standard deviations of 2.3 km and 2.6 km, respectively. For both the 1.0 km and 1.5 km peer group, coefficient estimates of peer effects are positive and statistically significant at 1 percent. Looking across columns 3-4, coefficient estimates are close to the estimates obtained from the 25 nearest neighbor peer group definition. The smaller magnitude point estimate on the 1.5 km peer group specification is consistent with our earlier finding that peer effects diminish with distance. The coefficients on the hydrological, climate, and price covariates are generally similar to our primary results in Tables 2 and 3. One exception is the coefficient on degree days over 32 Celsius, which is positive and significant at the 10 percent level or better. This is consistent with irrigation being a form of climate adaptation.

Lastly, we define the peer group at the level of the SD but reserve these results to an online appendix. The SD is a potentially significant source of socioeconomic interaction, especially in rural communities. At the SD level, coefficient estimates of peer effects are positive (though small in magnitude) and statistically significant at 5 percent or better when SD effects are excluded. Including SD effects results in the point estimate on the lagged number of adopters to not be statistically significant. This is not surprising given the large areal definition of a SD as the relevant peer group, especially in western Kansas where SD are large and groundwater is most prevalent (Fig. 2). As previously mentioned, estimates based on the SD may also be subject to some measurement error because of bias for growers on the boundary of a district (e.g. areal bias) (Fotheringham and Wong, 1991). Additionally, unobserved time-invariant factors at the SD level that are negatively (positively) correlated with the number of adopters would result in an estimate that is larger (smaller) in magnitude than the true causal effect because the installed base would proxy for the unobservables. This could be the case, for instance, if some SDs inherently have more proclivity to agricultural experimentation. Comparing columns 1-3 and 4-5 provides some evidence that this might in fact be the case. In sum, these results underscore the importance of exploiting individual-level panel data which allows for peer group fixed effects rather than aggregate or cross sectional data as there is tendency to mistake unobserved factors for peer effects.

Conclusion

This paper studies the role of peer effects using unique and highly disaggregated data on groundwater rights for agricultural irrigation in Kansas. We find strong evidence for causal peer effects, indicating that an additional groundwater adopter within the peer group increases the relative odds of adoption by 9 percent on average. The relative odds estimates translate into an increase in the probability of adoption from 2 percent with zero neighboring adopters to 5 percent with 10 (of 13) neighboring adopters. These peer effects appear to diminish over distance. We find some evidence that climate is a factor in the adoption of groundwater, consistent with narratives that groundwater is a mechanism for climate adaptation. These findings have clear policy relevance for decision makers who strive to steer and accelerate adoption of social desirable technologies.

Tables

Table 1. Summary statistics*

Variable (units)	Definition	Mean	Std.D	Min	Max
Stream Distance (meters)	Distance from location to nearest major stream	36,845.2	30,893.6	0.0	127,651.2
Precipitation (mm)	Five year moving average of annual rainfall	417.6	109.0	182.7	1,027.4
Degree days over 32C (degrees*days)	Five year moving average of annual count of time spent greater than 32C	42.6	13.5	5.8	105.3
Degree days between 8 and 32C (degrees*days)	Five year moving average of annual count of time spent greater than 8C and less than 32C	2,057.3	129.3	1,668.1	2,423.8
Palmer Drought Severity Index (PDSI)	Five year moving average of April-September PDSI	0.7	1.5	-4.4	3.1
Corn Price ($/bu)	Five year moving average of cash received, Kansas	7.8	4.0	2.9	17.6
Wheat Price ($/bu)	Five year moving average of cash received, Kansas	9.5	4.6	3.8	19.5
Predevelopment depth to water (feet)	Distance from surface to top of water table prior to groundwater development	80.5	56.2	0.0	277.0
Predevelopment saturated thickness (feet)	Extent of saturated portion of aquifer prior to groundwater development	186.5	118.6	0.0	619.7
Specific Yield	Aquifer yield ratio	16.6	3.5	5.0	25.0
Hydraulic Conductivity (ft/day)	Ease with which water moves through aquifer	277.8	95.1	45.9	476.3
Slope (%)	Soil slope	2.1	2.6	0.0	24.3
Elevation (meters)	Distance above sea level	786.4	273.3	202.7	1,631.0
Available Water Capacity (cm/cm)	Amount of water in soil available to plants	17.00	4.00	5.00	23.00
Soil Erodibility Factor (%)	Susceptibility of erosion by water	37.0	9.9	2.0	62.2
Carbonate (%)	Quantity of carbonate in soild	3.7	3.2	0.0	30.0
Sodium Absorption Ration (%)	Amount of sodium relative to calcium and magnesium	0.4	1.7	0.0	27.2
Soil Reaction (pH)	Soil pH level	7.5	0.5	5.2	8.5

Soil Organic Carbon (g/m^2)	Total organic carbon in soil	9,028.6	3,809.1	221.8	26,855.6
National Commodity Crop Productivity Index - Corn/Soybeans (%)	Soil productivity measure for corn/soybeans	34.5	13.3	1.1	89.1
National Commodity Crop Productivity Index - Small Grains (%)	Soil productivity measure for small grains	34.9	11.1	1.0	82.1
National Commodity Crop Productivity Index - Cotton (%)	Soil productivity measure for cotton	11.6	14.8	0.0	67.6
Root Zone Depth (cm)	Depth to which crops can extract water/nutrients	149.5	7.3	2.3	151.0
Root Zone Available Water Storage (mm)	Volume of plant available storage in root zone	254.2	50.7	4.7	335.0
Wind Erodibility Index (tons/acre/year)	Susceptibility of soil erosion from wind	71.5	33.0	0.0	250.0
Sand Total (%)	Total sand per unit soil	31.1	23.5	2.0	97.4
Silt Total (%)	Total silt per unit soil	45.3	18.3	0.6	71.8
Organic Matter (%)	Total organic matter per unit soil	0.8	0.3	0.1	2.8
Bulk Density (g/cm^3)	Weight of soil per unit volume	1.4	0.1	1.2	1.8
Drought Soil Landscape (in)	Drought vulnerable soils, binary 0,1	0.1	0.2	0.0	1.0

* The summary statistics are based on a balanced panel of 22,541 water right identifications over 64 years (1951-2014), resulting in a sample size of 1,442,624.

Table 2. Odds ratios for primary specifications for the 13 nearest neighbors by distance peer group.

	GMD FE	GMD FE and time trends	GMD FE and time trends, cce	GMD and SD FE, cce	SD FE, GMD time trends, cce
	(1)	(2)	(3)	(4)	(5)
Lagged number of adopters	1.091***	1.091***	1.084***	1.102***	1.100***
	(0.0099)	(0.0096)	(0.0108)	(0.0079)	(0.0073)
State time trend	1.099***	1.080***	1.009	1.032***	1.029***
	(0.0047)	(0.0070)	(0.0090)	(0.0046)	(0.0050)
Stream distance	1.000	1.000	1.000	1.000	1.000
	(1.01E-06)	(9.48E-07)	(8.84E-07)	(1.72E-06)	(1.78E-06)
Average distance to neighbors	1.000***	1.000***	1.000***	1.000***	1.000***
	(1.93E-05)	(1.89E-05)	(1.92E-05)	(1.57E-05)	(1.50E-05)
Palmer drought severity index	1.012	1.031	0.964	0.969	0.972
	(0.0244)	(0.0281)	(0.0291)	(0.0208)	(0.0218)
Precipitation	0.998**	0.998***	1.000	1.001	1.001
	(0.0007)	(0.0007)	(0.0008)	(0.0006)	(0.0006)
Degree days over 32C	0.981***	0.981***	1.004	1.004	1.004
	(0.0030)	(0.0031)	(0.0033)	(0.0025)	(0.0026)
Degree days between 8C and 32C	1.002***	1.002***	0.999	1.002***	1.002***
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0005)
Corn price	1.768***	1.783***	1.238***	1.330***	1.335***
	(0.0908)	(0.0933)	(0.0757)	(0.0584)	(0.0549)
Wheat price	0.846***	0.839***	0.859***	0.861***	0.862***
	(0.0236)	(0.0242)	(0.0241)	(0.0191)	(0.0186)
Predevelopment depth to water	0.999**	0.999**	0.999*		
	(4.63E-04)	(4.76E-04)	(4.67E-04)		
Predevelopment saturated thickness	0.999***	0.999***	0.999***		
	(2.93E-04)	(3.25E-04)	-(3.21E-04)		
Specific yield	0.991*	0.991**	0.991**		

	(0.0048)	(0.0048)	(0.0047)
Hydraulic conductivity	1.001***	1.001***	1.000**
	(0.0002)	(0.0002)	(0.0002)
Slope	0.978**	0.981**	0.975***
	(0.0090)	(0.0093)	(0.0091)
Elevation	1.000	1.000	1.000
	(1.16E-04)	(1.17E-04)	(1.12E-04)
Available water capacity	0.791	0.792	0.481
	(1.396)	(1.355)	(0.807)
Soil erodibility factor	0.988	0.989	0.987*
	(0.0076)	(0.0076)	(0.0076)
Carbonate	0.974***	0.969***	0.975***
	(0.0090)	(0.0096)	(0.0093)
Sodium absorption ratio	0.996	0.995	0.994
	(0.0092)	(0.0092)	(0.0093)
Soil reaction	1.027	1.027	0.993
	(0.0818)	(0.0841)	(0.0853)
Soil organic carbon	1.000	1.000	1.000
	(1.37E-05)	(1.34E-05)	(1.27E-05)
National commodity crop productivity index - corn/soybeans	1.01	1.01	1.007
	(0.0073)	(0.0071)	(0.0070)
National commodity crop productivity index - small grains	0.970***	0.969***	0.974***
	(0.0082)	(0.0082)	(0.0081)
National commodity crop productivity index - cotton	0.993***	0.993***	0.994***
	(0.0015)	(0.0016)	(0.0015)
Root zone depth	1.006**	1.005**	1.005**
	(0.0024)	(0.0024)	(0.0022)
Root zone available water storage	1.002*	1.002	1.002
	(0.0013)	(0.0013)	(0.0012)

Wind erodibility index	1.000	1.000	0.999		
	(0.0009)	(0.0009)	(0.0009)		
Sand total	1.001	1.001	1.000		
	(0.0042)	(0.0043)	(0.0040)		
Silt total	1.017**	1.016**	1.014**		
	(0.0070)	(0.0069)	(0.0066)		
Organic matter	1.196	1.193	1.16		
	(0.1840)	(0.1850)	(0.1700)		
Bulk density	0.168***	0.173***	0.163***		
	(0.0510)	(0.0579)	(0.0566)		
Drought soil landscape	1.747***	1.693***	1.601***		
	(0.176)	(0.179)	(0.165)		
Statewide adoption			107,665***	395.3***	737.0***
			(147,049)	(194.9)	(390.5)
GMD 1 adoption			50.89**	18.05***	46.26***
			(90.9)	(16.60)	(46.97)
GMD 2 adoption			6.179	5.584*	2.9
			(9.33)	(5.23)	(3.66)
GMD 3 adoption			84.33***	454.4***	105.8***
			(123.10)	(335.2)	(91.5)
GMD 4 adoption			33.47***	79.73***	47.14***
			(40.78)	(64.73)	(37.64)
GMD 5 adoption			21.60**	634.1***	47.34***
			(30.19)	(618.3)	(43.9)
Constant	6.94e-05***	0.000136***	1.026	1.77e-05***	7.25e-06***
	(1.21E-04)	(2.22E-04)	(1.84)	(2.98E-05)	(8.60E-06)
R^2	0.14	0.14	0.15	0.14	0.14
Observations	399,919	399,919	399,919	746,719	746,719

Standard errors clustered at SD in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3. Odds ratios for primary specifications for the 25 nearest neighbors by distance peer group.

	GMD FE (1)	GMD FE and time trends (2)	GMD FE and time trends, cce (3)	GMD and SD FE, cce (4)	SD FE, GMD time trends, cce (5)
Lagged number of adopters	1.052***	1.052***	1.048***	1.059***	1.058***
	(0.0059)	(0.0058)	(0.0066)	(0.0049)	(0.0045)
State time trend	1.095***	1.075***	1.005	1.028***	1.025***
	(0.0051)	(0.0073)	(0.0094)	(0.0049)	(0.0052)
Stream distance	1.000	1.000	1.000	1.000	1.000
	(1.01E-06)	(9.36E-07)	(8.69E-07)	(1.56E-06)	(1.63E-06)
Average distance to neighbors	1.000***	1.000***	1.000***	1.000***	1.000***
	(1.90E-05)	(1.89E-05)	(1.84E-05)	(1.35E-05)	(1.28E-05)
Palmer drought severity index	1.009	1.029	0.963	0.966	0.97
	(0.0241)	(0.0280)	(0.0290)	(0.0207)	(0.0219)
Precipitation	0.998***	0.998***	1.000	1.001	1.001
	(0.0007)	(0.0007)	(0.0008)	(0.0006)	(0.0006)
Degree days over 32C	0.980***	0.980***	1.003	1.003	1.003
	(0.0030)	(0.0031)	(0.0033)	(0.0026)	(0.0026)
Degree days between 8C and 32C	1.002***	1.002***	0.999	1.002***	1.002***
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0005)
Corn price	1.756***	1.773***	1.233***	1.322***	1.329***
	(0.0911)	(0.0937)	(0.0761)	(0.0588)	(0.0554)
Wheat price	0.849***	0.840***	0.861***	0.863***	0.864***
	(0.0240)	(0.0245)	(0.0243)	(0.0194)	(0.0189)
Predevelopment depth to water	0.999*	0.999*	0.999		
	(4.33E-04)	(4.45E-04)	(4.41E-04)		
Predevelopment saturated thickness	0.999***	0.999***	0.999***		
	(2.82E-04)	(3.16E-04)	(3.15E-04)		
Specific yield	0.993	0.992*	0.992*		

	(0.0044)	(0.0045)	(0.0044)
Hydraulic conductivity	1.000**	1.000**	1.000*
	(0.0002)	(0.0002)	(0.0002)
Slope	0.976***	0.979**	0.973***
	(0.0087)	(0.0089)	(0.0088)
Elevation	1.000	1.000	1.000
	(1.13E-04)	(1.14E-04)	(1.10E-04)
Available water capacity	0.949	0.936	0.565
	(1.6780)	(1.6130)	(0.9520)
Soil erodibility factor	0.988	0.989	0.987*
	(0.0077)	(0.0077)	(0.0077)
Carbonate	0.975***	0.970***	0.976***
	(0.0089)	(0.0094)	(0.0093)
Sodium absorption ratio	0.995	0.994	0.993
	(0.0091)	(0.0092)	(0.0092)
Soil reaction	1.060	1.061	1.025
	(0.0846)	(0.0871)	(0.0885)
Soil organic carbon	1.000	1.000	1.000
	(1.32E-05)	(1.31E-05)	(1.24E-05)
National commodity crop productivity index - corn/soybeans	1.009	1.01	1.007
	(0.0069)	(0.0067)	(0.0067)
National commodity crop productivity index - small grains	0.972***	0.971***	0.975***
	(0.0079)	(0.0079)	(0.0078)
National commodity crop productivity index - cotton	0.993***	0.993***	0.994***
	(0.0014)	(0.0016)	(0.0015)
Root zone depth	1.006**	1.005**	1.004*
	(0.0024)	(0.0024)	(0.0022)
Root zone available water storage	1.002*	1.002	1.002
	(0.0012)	(0.0012)	(0.0012)

Wind erodibility index	1.001	1.000	1.000		
	(0.0009)	(0.0009)	(0.0009)		
Sand total	1.001	1.000	0.999		
	(0.0041)	(0.0042)	(0.0039)		
Silt total	1.017**	1.016**	1.014**		
	(0.0070)	(0.0069)	(0.0066)		
Organic matter	1.136	1.133	1.105		
	(0.1740)	(0.1760)	(0.1620)		
Bulk density	0.192***	0.198***	0.186***		
	(0.0583)	(0.0664)	(0.0647)		
Drought soil landscape	1.711***	1.662***	1.575***		
	(0.168)	(0.170)	(0.156)		
Statewide adoption			139,246***	451.5***	820.4***
			(189,322)	(224.1)	(438.5)
GMD 1 adoption			35.42**	11.40***	37.51***
			(63.27)	(10.24)	(38.73)
GMD 2 adoption			5.32	5.708*	2.880
			(8.045)	(5.404)	(3.73)
GMD 3 adoption			55.22***	324.5***	79.69***
			(80.18)	(237.0)	(69.50)
GMD 4 adoption			23.04***	57.21***	37.77***
			(27.82)	(46.50)	(30.13)
GMD 5 adoption			17.17**	554.1***	46.46***
			(23.70)	(534)	(42.40)
Constant	6.68e-05***	0.000133***	0.943	2.40e-05***	9.93e-06***
	(1.18E-04)	(2.21E-04)	(1.72)	(4.10E-05)	(1.20E-05)
R^2	0.14	0.14	0.15	0.14	0.14
Observations	399,919	399,919	399,919	746,719	746,719

Standard errors clustered at SD in parentheses

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

Table 4. Response margins for adoption evaluated at different numbers of lagged adopters in the peer group. *

	13 Nearest Neighbors						25 Nearest Neighbors					
	GMD FE and time trends, cce		GMD and SD FE, cce		SD FE, GMD time trends, cce		GMD FE and time trends, cce		GMD and SD FE, cce		SD FE, GMD time trends, cce	
Lagged number of adopters	Margin	Std. Err	Margin	Std. Err	Margin	Std. Err	Margin	Std. Err	Margin	Std. Err	Margin	Std. Err
0	0.0219	1.07E-03	0.0192	5.89E-04	0.0193	5.46E-04	0.0212	1.14E-03	0.0185	6.88E-04	0.0186	6.35E-04
1	0.0239	9.93E-04	0.0213	5.28E-04	0.0213	4.95E-04	0.0223	1.08E-03	0.0196	6.50E-04	0.0197	0.00E+00
5	0.0334	1.08E-03	0.0316	6.31E-04	0.0313	6.28E-04	0.0273	8.83E-04	0.0246	4.86E-04	0.0247	4.61E-04
10	0.0507	3.31E-03	0.0514	2.46E-03	0.0503	2.32E-03	0.0351	1.18E-03	0.0330	6.84E-04	0.0326	6.78E-04
12	0.0597	4.89E-03	0.0622	3.75E-03	0.0607	3.51E-03	0.0388	1.58E-03	0.0370	9.99E-04	0.0365	9.70E-04
15							0.0450	2.47E-03	0.0440	1.68E-03	0.0431	1.59E-03
20							0.0576	4.67E-03	0.0582	3.40E-03	0.0566	3.15E-03
24							0.0699	7.16E-03	0.0728	5.40E-03	0.0703	4.94E-03

* Calculated at the means of all covariates.

Table 5. Intensifying peer effect with hydraulic conductivity.

	13 nearest neighbors (1)	25 nearest neighbors (2)
Lagged number of adopters	1.063**	1.035**
	(0.0300)	(0.0170)
1 lagged adopters # hydraulic conductivity	1.001***	1.002***
	(2.32E-04)	(2.61E-04)
2 lagged adopters # hydraulic conductivity	1.002***	1.002***
	(3.05E-04)	(3.07E-04)
3 lagged adopters # hydraulic conductivity	1.002***	1.002***
	(3.78E-04)	(3.27E-04)
4 lagged adopters # hydraulic conductivity	1.002***	1.002***
	(4.42E-04)	(4.16E-04)
5 lagged adopters # hydraulic conductivity	1.002***	1.002***
	(4.94E-04)	(4.50E-04)
6 lagged adopters # hydraulic conductivity	1.002***	1.002***
	(5.26E-04)	(4.42E-04)
7 lagged adopters # hydraulic conductivity	1.002***	1.003***
	(6.54E-04)	(5.19E-04)
8 lagged adopters # hydraulic conductivity	1.002***	1.003***
	(7.05E-04)	(5.10E-04)
9 lagged adopters # hydraulic conductivity	1.002**	1.003***
	(7.52E-04)	(5.73E-04)
10 lagged adopters # hydraulic conductivity	1.002**	1.003***
	(8.01E-04)	(5.71E-04)
11 lagged adopters # hydraulic conductivity	1.002**	1.003***
	(8.64E-04)	(6.46E-04)
12 lagged adopters # hydraulic conductivity	1.002*	1.003***
	(1.02E-03)	(6.71E-04)
13 lagged adopters # hydraulic conductivity	1.001	1.003***
	(1.06E-03)	(7.02E-04)
14 lagged adopters # hydraulic conductivity		1.003***
		(7.58E-04)
15 lagged adopters # hydraulic conductivity		1.002***
		(7.74E-04)
16 lagged adopters # hydraulic conductivity		1.003***
		(7.69E-04)
17 lagged adopters # hydraulic conductivity		1.003***
		(8.53E-04)

18 lagged adopters # hydraulic conductivity		1.003***
		(8.89E-04)
19 lagged adopters # hydraulic conductivity		1.003***
		(9.11E-04)
20 lagged adopters # hydraulic conductivity		1.003***
		(8.94E-04)
21 lagged adopters # hydraulic conductivity		1.003***
		(9.92E-04)
22 lagged adopters # hydraulic conductivity		1.003***
		(0.0010)
23 lagged adopters # hydraulic conductivity		1.002**
		(0.0010)
24 lagged adopters # hydraulic conductivity		1.002*
		(0.0012)
25 lagged adopters # hydraulic conductivity		1.002
		(0.0013)
State time trend	1.012	1.008
	(0.0082)	(0.0084)
Stream distance	1.000	1.000
	(8.76E-07)	(8.73E-07)
Average distance to neighbors	1.000***	1.000***
	(1.99E-05)	(1.87E-05)
Palmer drought severity index	0.949*	0.943*
	(0.0285)	(0.0284)
Precipitation	1.000	1.000
	(7.94E-04)	(7.83E-04)
Degree days over 32C	1.005	1.006*
	(0.0033)	(0.0033)
Degree days between 8C and 32C	0.999**	0.999**
	(4.65E-04)	(4.65E-04)
Corn price	1.221***	1.216***
	(0.0753)	(0.0762)
Wheat price	0.876***	0.882***
	(0.0240)	(0.0244)
Predevelopment depth to water	0.999*	1.000
	(4.54E-04)	(4.28E-04)
Predevelopment saturated thickness	0.999***	0.999***
	(3.25E-04)	(3.22E-04)
Specific yield	0.990**	0.991*
	(0.0047)	(0.0046)

Hydraulic conductivity	0.999	0.998***
	(6.80E-04)	(7.36E-04)
Slope	0.978**	0.975***
	(0.0096)	(0.0095)
Elevation	1.000	1.000
	(1.14E-04)	(1.11E-04)
Available water capacity	0.491	0.566
	(0.8320)	(0.9600)
Soil erodibility factor	0.987*	0.987*
	(0.0076)	(0.0077)
Carbonate	0.975***	0.977**
	(0.0092)	(0.0091)
Sodium absorption ratio	0.996	0.996
	(0.009)	(0.009)
Soil reaction	0.971	0.983
	(0.0836)	(0.0869)
Soil organic carbon	1.000	1.000
	(1.28E-05)	(1.26E-05)
National commodity crop productivity index - corn/soybeans	1.008	1.008
	(7.07E-03)	(6.88E-03)
National commodity crop productivity index - small grains	0.973***	0.974***
	(0.0081)	(0.0080)
National commodity crop productivity index - cotton	0.994***	0.995***
	(0.0015)	(0.0015)
Root zone depth	1.005**	1.005**
	(0.0023)	(0.0023)
Root zone available water storage	1.002	1.002
	(0.0012)	(0.0011)
Wind erodibility index	0.999	1.000
	(0.0009)	(0.0009)
Sand total	1.000	0.999
	(0.0040)	(0.0039)
Silt total	1.015**	1.014**
	(0.0066)	(0.0064)
Organic matter	1.157	1.114
	(0.170)	(0.162)
Bulk density	0.162***	0.188***
	(0.0556)	(0.0659)
Drought soil landscape	1.659***	1.636***
	(0.181)	(0.171)
Constant	1.404	1.666

	(2.404)	(2.941)
R^2	0.15	0.15
Observations	399,919	399,918

Standard errors clustered at SD in parentheses

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

Table 6. Linear probability model and 1.0 and 1.5 km estimates.

	13 nearest neighbors (1)	25 nearest neighbors (2)	1.0 km (3)	1.5 km (4)
Lagged number of adopters	0.0150***	0.00935***	1.061***	1.051***
	(0.0007)	(0.0004)	(0.0203)	(0.0162)
State time trend	0.00550***	0.00475***	1.025***	1.022**
	(0.0008)	(0.0008)	(0.0092)	(0.0090)
Stream distance			1.000	1.000
			(1.13E-06)	(1.10E-06)
Palmer drought severity index	0.0201***	0.0201***	0.97	0.97
	(0.0029)	(0.0029)	(0.0303)	(0.0297)
Precipitation	1.590E-05	7.210E-06	1.000	1.000
	(3.21E-05)	(2.81E-05)	(0.0009)	(0.0008)
Degree days over 32C	0.00112***	0.000979***	1.008**	1.006*
	(2.16E-04)	(2.01E-04)	(0.0035)	(0.0035)
Degree days between 8C and 32C	-9.82e-05**	-6.86e-05*	0.999**	0.999*
	(4.24E-05)	(3.97E-05)	(0.0005)	(0.0005)
Corn price	0.0384***	0.0384***	1.271***	1.267***
	(0.0057)	(0.0058)	(0.0760)	(0.0758)
Wheat price	-0.00447***	-0.00461***	0.850***	0.852***
	(0.0011)	(0.0011)	(0.0238)	(0.0236)
Predevelopment depth to water	-0.00447***		0.998***	0.998***
	(0.0011)		(5.94E-04)	(5.74E-04)
Predevelopment saturated thickness			0.999**	0.999**

	(4.14E-04)	(4.15E-04)
Specific yield	0.990*	0.989*
	(0.0060)	(0.0057)
Hydraulic conductivity	1.001**	1.001***
	(0.0003)	(0.0003)
Slope	0.958***	0.963***
	(0.0103)	(0.0102)
Elevation	1.000	1.000
	(1.39E-04)	(1.32E-04)
Available water capacity	0.121	0.184
	(0.2250)	(0.3330)
Soil erodibility factor	0.985	0.984*
	(0.0096)	(0.0087)
Carbonate	0.973**	0.975**
	(0.0112)	(0.0107)
Sodium absorption ratio	0.987	0.989
	(0.0109)	(0.0102)
Soil reaction	0.926	0.931
	(0.0932)	(0.0931)
Soil organic carbon	1.000	1.000*
	(1.35E-05)	(1.38E-05)
National commodity crop productivity index - corn/soybeans	1.008	1.007
	(0.0085)	(0.0083)
National commodity crop productivity index - small grains	0.969***	0.970***
	(0.0098)	(0.0095)
National commodity crop productivity index - cotton	0.993***	0.994***
	(0.0018)	(0.0017)

Root zone depth			1.006*	1.005
			(0.0030)	(0.0028)
Root zone available water storage			1.002	1.002*
			(0.0015)	(0.0014)
Wind erodibility index			0.999	0.999
			(0.0011)	(0.0010)
Sand total			1.002	1.002
			(0.0049)	(0.0047)
Silt total			1.020**	1.020***
			(0.0080)	(0.0074)
Organic matter			1.287	1.302
			(0.2090)	(0.2120)
Bulk density			0.0731***	0.0772***
			(0.0272)	(0.0302)
Drought soil landscape			1.642***	1.602***
			(0.185)	(0.180)
Statewide adoption			51,464***	60,108***
			(69,555)	(82,155)
GMD 1 adoption			162.8***	94.30***
			(270.9)	(163.3)
GMD 2 adoption			7.231	7.074
			(10.78)	(10.62)
GMD 3 adoption			221.6***	221.7***
			(318.9)	(330.7)
GMD 4 adoption			78.80***	78.18***
			(94.72)	(97.20)
GMD 5 adoption			35.05***	32.84**
			(47.68)	(45.56)
Constant	-0.298***	-0.337***	3.841	2.801

	(0.107)	(0.103)	(7.524)	(5.525)
R^2	0.11	0.11	0.14	0.15
Observations	746,780	741,829	351,461	387,549

Standard errors clustered at SD in parentheses

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

Figures

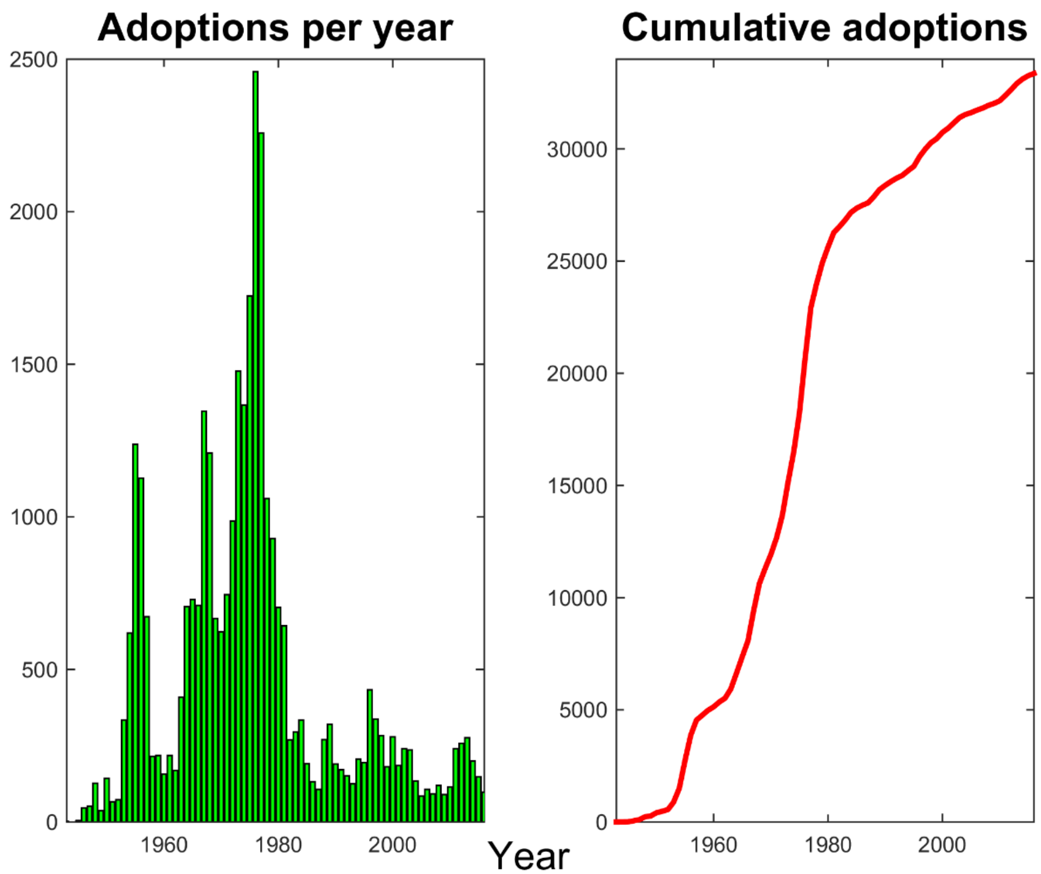

Figure 1. New groundwater adoptions per year (left) and cumulative adoptions over time (right).

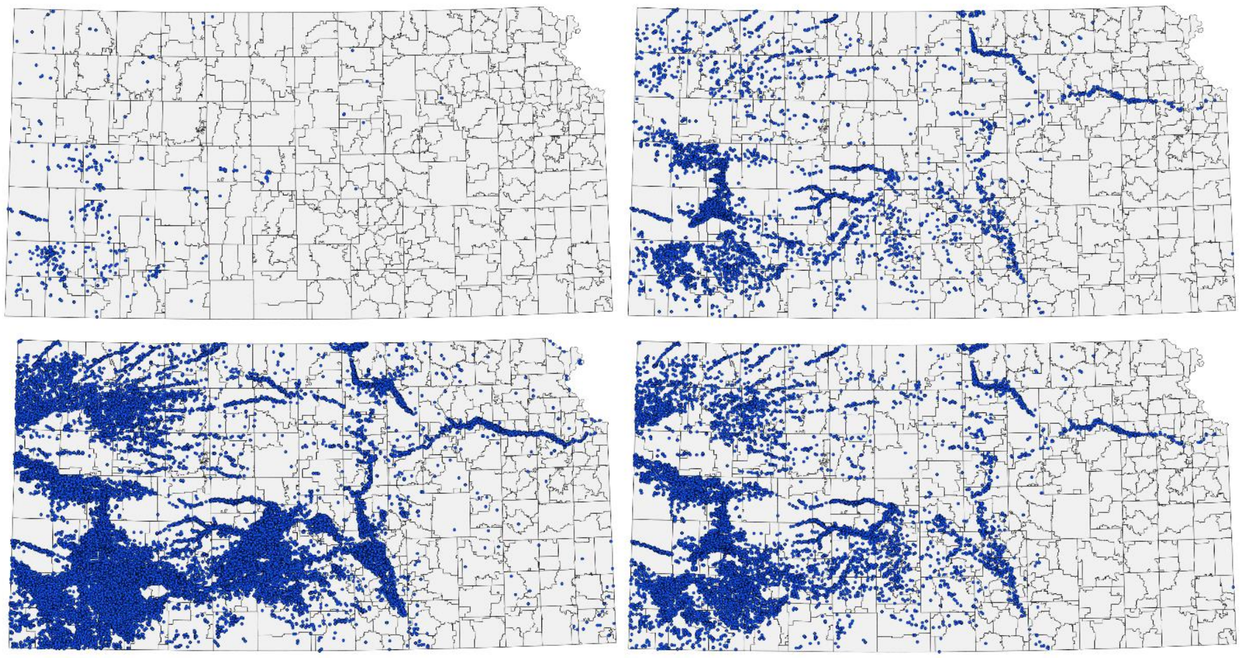

Figure 2. Spatial pattern of groundwater adoption. Clockwise from top-left: 1950, 1960, 1970, 2000.

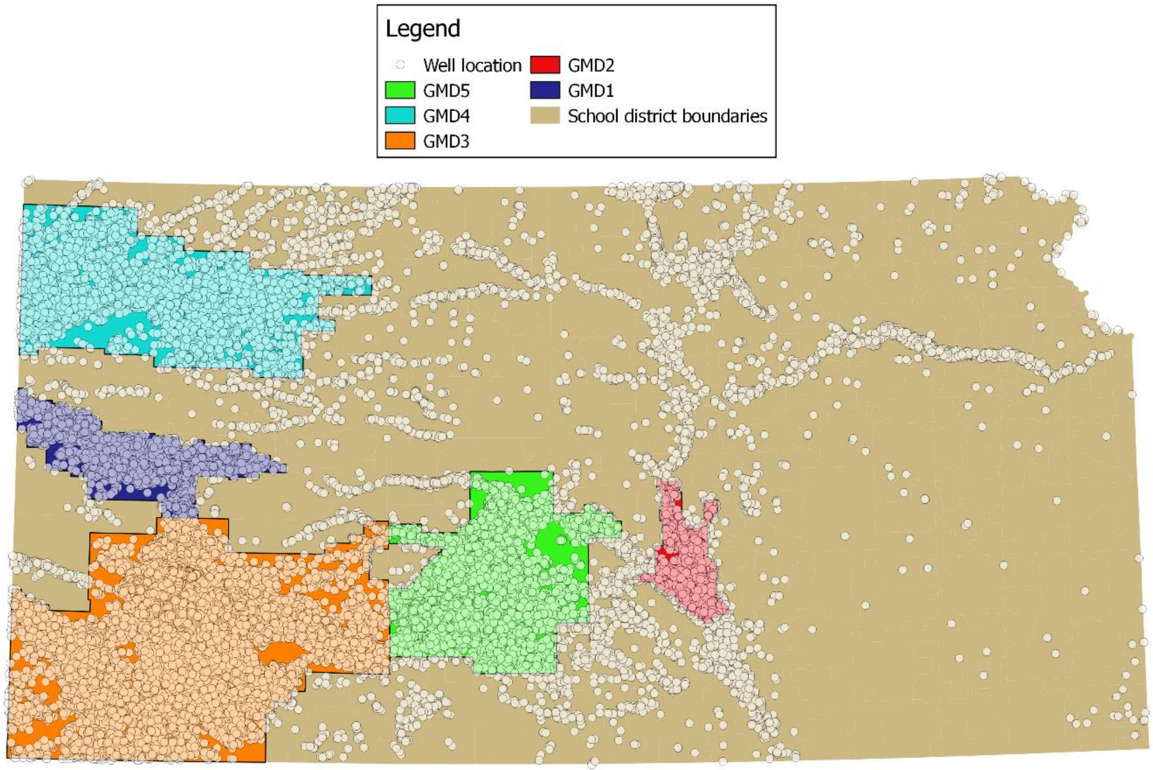

Figure 3. Location of GMDs and groundwater wells.

Monte Carlo Simulation

In order to investigate the impacts of omitting individuals that never adopt and omitting observations subsequent to the first time an individual acquired a right, we generated returns according to

$$\pi_{it} = \alpha x_{it} + \beta z_g + \gamma z_t + \delta y_{i(t-1)} + \varepsilon_{it}$$

where i denotes the individual, t the time period, and g the group. We simulated returns for 50 groups, each with 50 individuals, and each individual with 50 observations (i.e., $t = 50$), giving a total of 125,000 observations across 2,500 individuals. We drew each of the variables as follows: $x_{it} \sim N(0,6)$, $z_g \sim N(0,4)$, $z_t = -15 + 0.2t$, and $\varepsilon_{it} \sim \textit{IID Gumbel}$. We set $\alpha = 1$, $\beta = 1$, $\gamma = 1$, and $\delta = 0.5$. Adoption occurred when $\pi_{it} > 0$. Table A1 reports the average estimates for δ from 100 simulations when all observations are used, when observations for non-adopters are omitted, when post-adoption observations are omitted, and when both are omitted. The first thing to note is that even when all of the data is included, the peer effect estimate is slightly below the true value (column 1). We found that whenever there are individuals that never adopt, the peer effect estimate is attenuated downward, even when the observations for those individuals are included in estimation. Columns 2-4 show that omitting non-adopters observations and/or post-adoption observations only attenuates the estimate slight more downward.

Table A1. Simulation Results

True Value	All Observations	Omit non-Adopters	Omit post-adoption observations	Omit non-adopters and post-adoption observations
0.5	0.4626 (0.0064)	0.4615 (0.0065)	0.4402 (0.0116)	0.4434 (0.0120)

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