Agricultural and Resource Economics Review (2026), **55**, 124–144
doi:10.1017/age.2025.10017

RESEARCH ARTICLE

Peer effects in irrigation adoption in South Carolina

Dawoon Jeong[1] and Gabriela Perez-Quesada[2]

[1]Department of Agricultural Sciences, Clemson University, Clemson, SC, USA and [2]Department of Agricultural and Resource Economics, University of Tennessee, Knoxville, TN, USA
Corresponding author: Dawoon Jeong; Email: dawoonj@clemson.edu

(Received 19 January 2025; revised 11 November 2025; accepted 25 November 2025; first published online 13 January 2026)

Abstract

Irrigation can enhance yields and serve as a climate adaptation strategy. In the Southeastern U.S., where water resources are relatively abundant, irrigation has experienced significant growth. However, despite the region's capacity for further expansion, irrigation adoption rates remain low. This study estimates the influence of peer effects on farmers' decisions to adopt irrigation in South Carolina, using a unique parcel-level dataset on irrigation withdrawals. We find that adoption increases as farmers observe more peer adopting irrigation – social interactions – and as peers' pumping increases, such as during drought periods, when the benefits of irrigation become more visible, facilitating social learning.

Keywords: drought; irrigation adoption; peer effects; Southeastern agriculture

JEL codes: O33; Q15; Q16

Introduction

Irrigation is a climate-resilient farming practice that mitigates crop damage from weather shocks (Smith and Edwards 2021; Tack et al. 2017; Troy et al. 2015). In the United States, irrigation has traditionally been concentrated in the arid West, where precipitation is insufficient to meet crop water requirements. However, increasing water stress poses significant challenges to the long-term sustainability of irrigation-based agricultural systems (Deines et al. 2020; Mrad et al. 2020). In contrast, the Eastern United States – characterized by a more humid climate and variable rainfall – has relied on precipitation, with producers increasingly adopting supplemental irrigation during critical crop growth stages (Mullen et al. 2009). In addition, the relative abundance of water for irrigation in the East offers new opportunities to expand irrigated agriculture and potentially shift the focus of irrigation development (Mehta et al. 2024).

The Southeast is one of the fastest-growing regions for irrigation adoption in the U.S. (Hrozencik and Aillery 2022; Reidmiller et al. 2017), with South Carolina serving as a

© The Author(s), 2026. Published by Cambridge University Press on behalf of Northeastern Agricultural and Resource Economics Association. This is an Open Access article, distributed under the terms of the Creative Commons Attribution licence (https://creativecommons.org/licenses/by/4.0/), which permits unrestricted re-use, distribution and reproduction, provided the original article is properly cited.

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

notable example. Between 2002 and 2022, irrigated agricultural land in South Carolina increased by 25%, adding 20,000 irrigated acres across its four major crops such as corn, cotton, peanuts and soybeans. However, despite the region's potential for sustainable irrigation growth (Mehta et al. 2024; Rosa et al. 2020), adoption rates in the Southeast remain modest (Cooley and Smith 2022).

Farmers' reliance on traditional farming practices can lead to inertia, slowing the adoption rate of new irrigation technologies (Perry et al. 2022). Therefore, identifying the factors that drive irrigation adoption decisions is crucial for policymakers, particularly as droughts are projected to increase in frequency (Strzepek et al. 2010). This paper estimates the role of peer effects in shaping farmers' decisions to adopt irrigation in South Carolina, using a unique parcel-level dataset on irrigation withdrawals collected annually by the South Carolina Department of Environmental Services (SCDES).

We argue that *social interaction* and *social learning* are two key mechanisms through which peer effects influence irrigation adoption in South Carolina. Social interaction refers to situations in which an individual's benefit from taking an action increases when others take the same action, independent of any information exchange or learning (Cooper and Rege 2011; Lahno and Serra-Garcia 2015). We use the number of peer irrigators to measure peers' choices that may induce social interaction. This mechanism has been documented in irrigation adoption in arid agricultural systems such as Kansas (Sampson and Perry 2019b). In contrast, social learning could potentially play an important role in South Carolina. Because irrigation is typically used as a supplement to rainfall rather than as a year-round practice, farmers may differ in their understanding of the costs and benefits associated with adopting irrigation. Social learning occurs when individuals acquire information about the value of an action by observing the outcomes experienced by peers (Cooper and Rege 2011). For instance, a farmer may delay adoption until they observe clear evidence that irrigation has improved yields or reduced risk for their peers. We use peers' water use as a measure of the potential value of irrigation among irrigators. Opportunities for learning are likely to be greater during drought conditions, when increased pumping makes the value of irrigation more visible and salient.

There are three common sources of endogeneity that make the identification of peer effects challenging: self-selection of peer group, correlated unobservables, and simultaneity (i.e., reflection) (Bollinger and Gillingham 2012; Manski 1993b). To mitigate bias from self-selection we control for various contextual factors, such as farm characteristics, crop type, weather conditions that could drive irrigation adoption (Carey and Zilberman 2002; Hendricks and Peterson 2012; Schoengold et al. 2006; Smith et al. 2017). Additionally, to address bias from correlated unobservables, we incorporate a rich set of fixed effects to account for unobserved factors that may simultaneously affect both individual farmers and their peers. Finally, to reduce reflection bias, we define peer effect using the installed base – the cumulative count of peer irrigators up to the previous year. This approach ensures that only past irrigation decisions by peers can influence current adoption decisions, eliminating reverse causality (Bollinger and Gillingham 2012).

Our results provide evidence that both mechanisms – social interaction and social learning – can be relevant to irrigation adoption decisions among farmers who eventually adopt irrigation. Specifically, each additional peer irrigator increases the probability of adoption by 0.4 percentage points. We also find evidence of peer influence under conditions that enhance opportunities for learning about the value of irrigation. A 100 million gallon increase in peer irrigation water use is associated with a 0.3 percentage point increase in the probability of adoption. This finding suggests that as peers' pumping

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

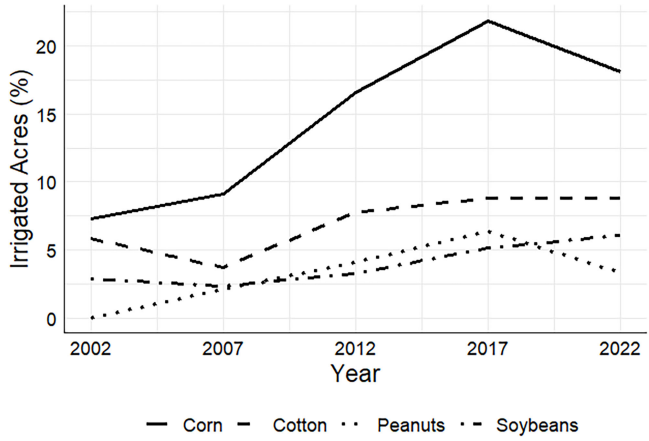


Figure 1. Trends in irrigated acreages by crops in South Carolina. Notes: The percentage of irrigated acres for each crop is calculated by dividing the number of irrigated harvested acres by the total harvested acres for that crop.

increases – such as during drought conditions – the benefits of irrigation become more visible, thereby facilitating social learning and accelerating adoption.

Peer effects have gained growing attention as a key factor influencing the adoption of agricultural practices (Burlig and Stevens 2023; Che et al. 2022; Mart nez et al. 2022). In the context of irrigation technology adoption, existing evidence highlights the significant role of peer influences in acquiring groundwater rights and adopting water-saving irrigation technologies in Kansas (Sampson and Perry, 2019b,a). Building on this body of research, this study examines peer effects on irrigation adoption with a particular focus on the Southeastern United States. Our study also contributes to the existing literature on irrigation adoption (Carey and Zilberman 2002; Sampson and Perry 2019b), social interaction (Sampson and Perry 2019b), and social learning (Burlig and Stevens 2023; Erev and Roth 2014; Foster and Rosenzweig 1995), by examining the role of peer effect in shaping irrigation decisions. Unlike much of the existing research, which has predominantly examined irrigation practices in the arid Western U.S., this study focuses on a less-studied region, providing new insights into irrigation dynamics in the East.

Background

Irrigation trends and development in South Carolina

While irrigated land has decreased in the Western U.S. over the past two decades, the Eastern region has seen a significant expansion in irrigation practices (Hrozencik and Aillery 2022; Xie and Lark 2021). In South Carolina, this trend is particularly evident, with a significant increase in the irrigated acreage of major crops across the state. As Figure 1 shows, the percentage of irrigated corn acreage relative to the total harvested corn acres increased from 7.3% in 2002 to 18.1% in 2022. Similar upward trends in irrigation are observed for other crops, although to a lesser extent. For cotton, the percentage of irrigated harvested acres increased from 5.8% in 2002 to 8.8%, for peanuts from 0% to 3.3%, and for soybeans from 2.9% to 6.1%.

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

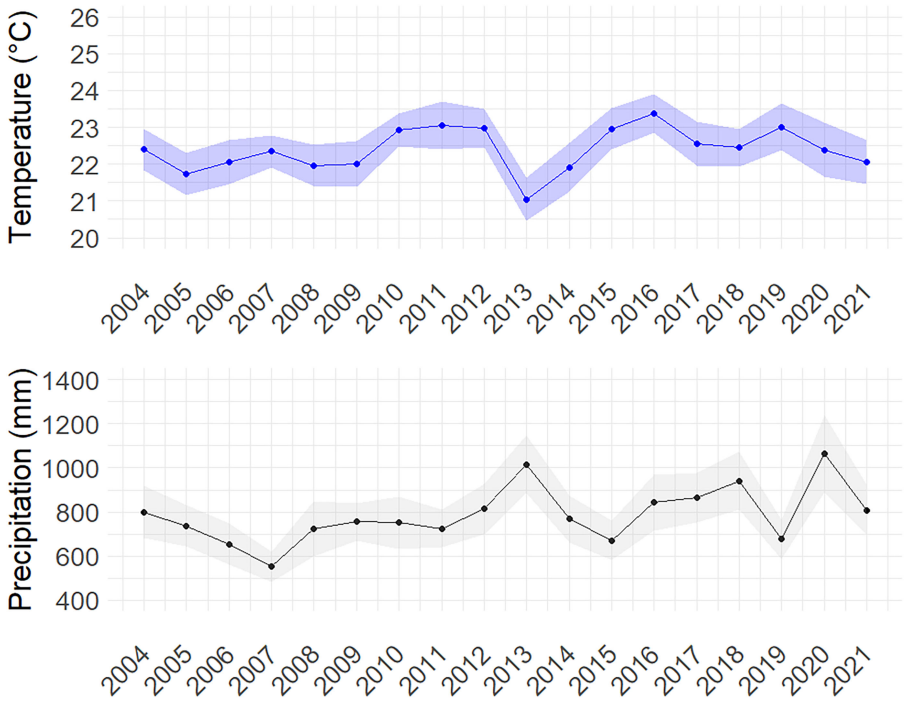


Figure 2. Average growing season temperature and precipitation in South Carolina. Notes: In the upper panel, the solid line is the average growing season temperature computed by daily temperature at the irrigation permit sites during the growing seasons from March to September each year. The shaded areas show one standard deviation from the mean. In the bottom panel, the solid line shows the average precipitation computed by cumulative annual precipitation across irrigation permit sites during the growing seasons from March to September each year. The shaded areas represent one standard deviation from the mean.

South Carolina's climate is characterized by moderate temperatures and abundant rainfall throughout the year, creating generally favorable conditions for agricultural production. The state has received an average annual precipitation of 787 mm since 2004 (Figure 2), with an average temperature of 22.4C. This relatively high level of precipitation is a key factor in understanding the growing demand for irrigation in South Carolina given that the drivers of irrigation adoption may differ from those in drier states like Kansas, where annual precipitation is nearly half (approximately 416 mm).

Although South Carolina generally receives adequate rainfall, it also experiences periodic droughts of varying severity and duration. Figure 3 illustrates drought conditions at irrigation permit sites across the state from 2004 to 2021. The figure presents the annual mean number of drought weeks at each severity level, ranging from Abnormally Dry (D0) to Exceptional Drought (D4), as defined by the U.S. Drought Monitor. Although the state generally experiences milder droughts, the duration and intensity of droughts vary substantially from year to year. The most severe drought events occurred in 2007, 2008, 2011, and 2012.

Over the past two decades, South Carolina has experienced significant growth in irrigation. Figure 4 shows the spatial distribution of irrigated agricultural land. Irrigation is primarily concentrated in the central regions and is unevenly distributed across counties, highlighting substantial regional heterogeneity in adoption patterns.

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

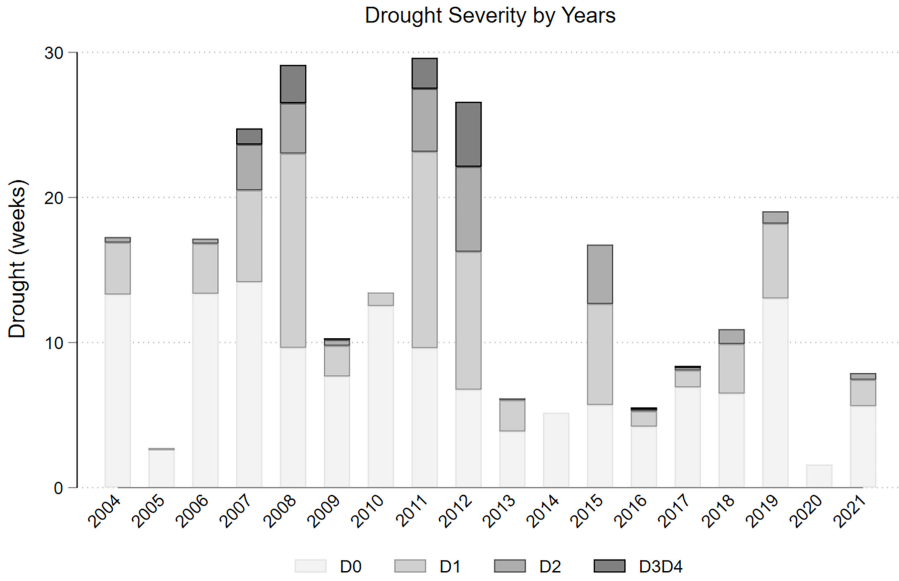


Figure 3. Drought severity in South Carolina. Notes: Each shade represents the annual average number of drought weeks across irrigation permit sites for the four drought severity categories. These categories, defined by the U.S. Drought Monitor, include Abnormally Dry (D0, lightest gray), Moderate Drought (D1, second lightest gray), Severe Drought (D2, darker gray), and Extreme/Exceptional Drought (D3 + D4, darkest gray). The bars are stacked to represent the total average number of drought weeks per year.

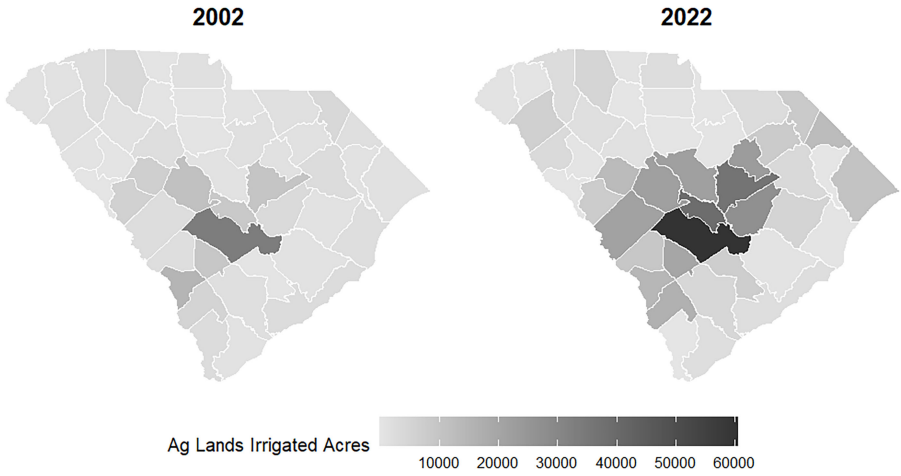


Figure 4. Spatial distribution of irrigated acres by county in 2002 and 2022. Notes: The map on the left shows the total irrigated land by county in 2002, while the map on the right shows the same for 2022. Darker gray shades indicate a higher concentration of irrigated land in each county. (Source: USDA NASS, Census of Agriculture).

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

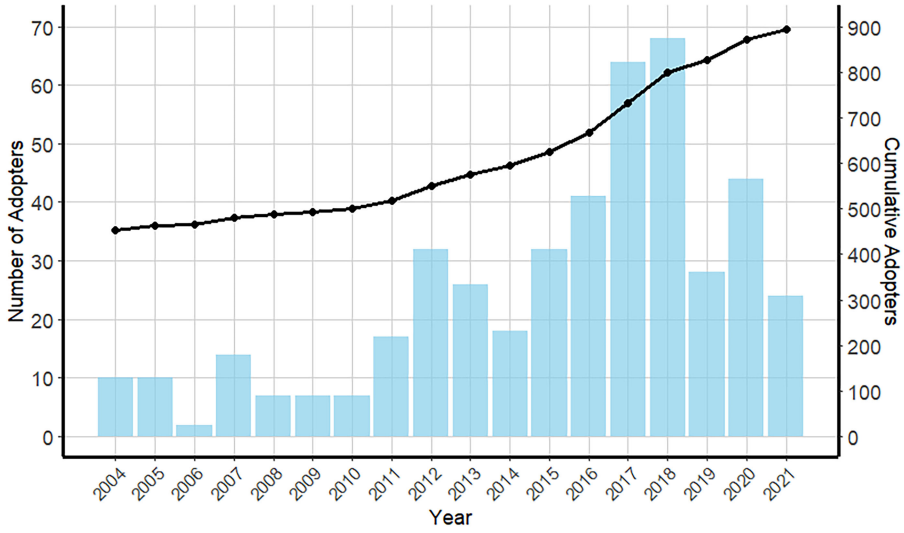


Figure 5. Trend of irrigation adoption in South Carolina. Notes: The bars show the number of annual irrigation adoptions from 2004 to 2021, and the solid line plots the cumulative number of adoptions by aggregating the annual figures in the top panel. The cumulative count includes 444 existing permit holders who adopted prior to 2004.

Figure 5 presents the trend in irrigation adoption in South Carolina. The top panel shows the annual number of new irrigation adopters between 2004 and 2021, while the bottom panel displays the cumulative number of adoptions since 1983, when South Carolina's water withdrawal reporting rule was established. Prior to 2004, there were 444 irrigation permits. Adoption increased significantly from 2004 to 2021, nearly doubling the cumulative total. This surge in adoption may be attributed to the severe droughts of 2011, as indicated by the weather and drought patterns in Figures 2 and 3, or it could reflect farmers' adaptive strategies in response to adverse weather, informed by past experiences. Alternatively, the increase could also be influenced by peer effects.

In South Carolina, irrigation is typically used as a supplement to rainfall rather than as a continuous, year-round practice, so water use tends to increase during drought periods. Figure 6 shows the relationship between drought conditions – measured by drought durations weighted by severity levels – and the corresponding irrigation groundwater usage, using annual averages from 2004 to 2021. In this context, peers' irrigation water use can provide valuable information that influences a farmer's decision to adopt irrigation.

Surface water has traditionally been the primary source of irrigation, but in recent years, groundwater has become increasingly dominant. Currently, 96% of new irrigation adopters rely on groundwater, while only 4% use surface water. As a result, irrigated farms are largely concentrated in regions where key aquifers are located, primarily east of the Fall Line, as shown in figure A1 in Supplementary Appendix A2. This area, known as the Coastal Plain, overlays the Atlantic Coastal Plain (ACP) aquifer system (Campbell et al. 2012). The ACP system consists of multiple layers of confined aquifers, with unconfined aquifers situated on top, each separated by impermeable materials. Between 2004 and 2021, 12 confined aquifers have been used for irrigation in South Carolina. More detailed information on these aquifers can be found in Supplementary Appendix A2.

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

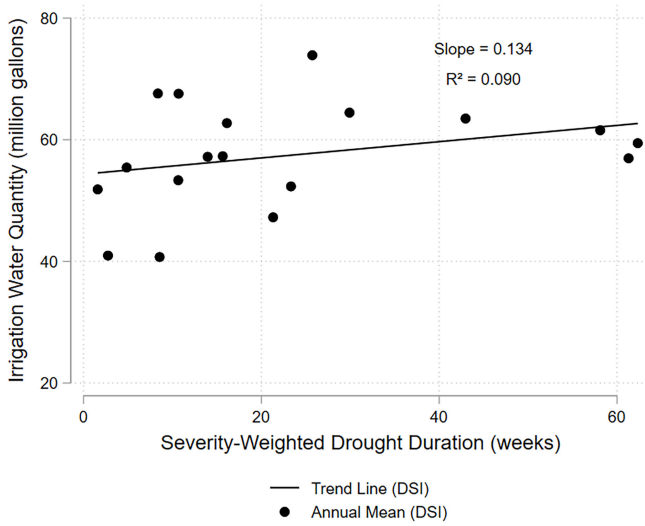


Figure 6. Relationship between drought duration and irrigation water usage. Notes: This figure shows the annual number of drought weeks, weighted by drought severity categories (D0 to D4), where the weights assigned to each category are: D0 = 1, D1 = 2, D2 = 3, D3 = 4, and D4 = 5, following the Drought Severity and Coverage Index methodology (Akyuz, 2017). These weighted values are plotted alongside the corresponding annual means of irrigation water usage (in million gallons) for each year from 2004 to 2021. Trend lines are included to illustrate the positive relationship between severity weighted drought durations and irrigation water usage.

Groundwater withdrawal regulation and reporting

South Carolina, as well as the rest of the states in the East of U.S., is governed by the riparian doctrine, in which water allocations are tied to the holding of land adjacent to a water source. However, South Carolina's water use and reporting regulations have undergone substantial changes over time (Nix and Rad 2022). Some of these changes are described next.

The South Carolina Groundwater Use Act was passed in 1969, establishing reporting requirements for groundwater withdrawals greater than or equal to 100,000 gallons on any day located within a Capacity Use Area (CUA). In 1993, amendments to the South Carolina Water Resources Planning and Coordination Act led to the dissolution of the South Carolina Water Resources Commission (Gellici 2011). Subsequently, its responsibilities were divided between two new entities: the South Carolina Department of Health and Environmental Control (SCDHEC), tasked with enforcing water regulations, and the South Carolina Department of Natural Resources, which leads water planning.[1] A mandatory reporting threshold of more than three million gallons (MG) in any one month was implemented in 2000 (Wachob et al. 2009). Lastly, in 2010, the South Carolina Surface Water Withdrawal, Permitting Use, and Reporting Act was passed and established a change in the South Carolina's water law from riparian water rights to a regulated riparianism system (Taylor 2018).

CUAs have been established over time to improve the effectiveness of monitoring and managing the use of aquifers across the state. There are currently six CUAs in place and the

[1]In 2024, certain divisions of SCDHEC and SCDNR have been reorganized under the South Carolina Department of Environmental Services (SCDES).

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

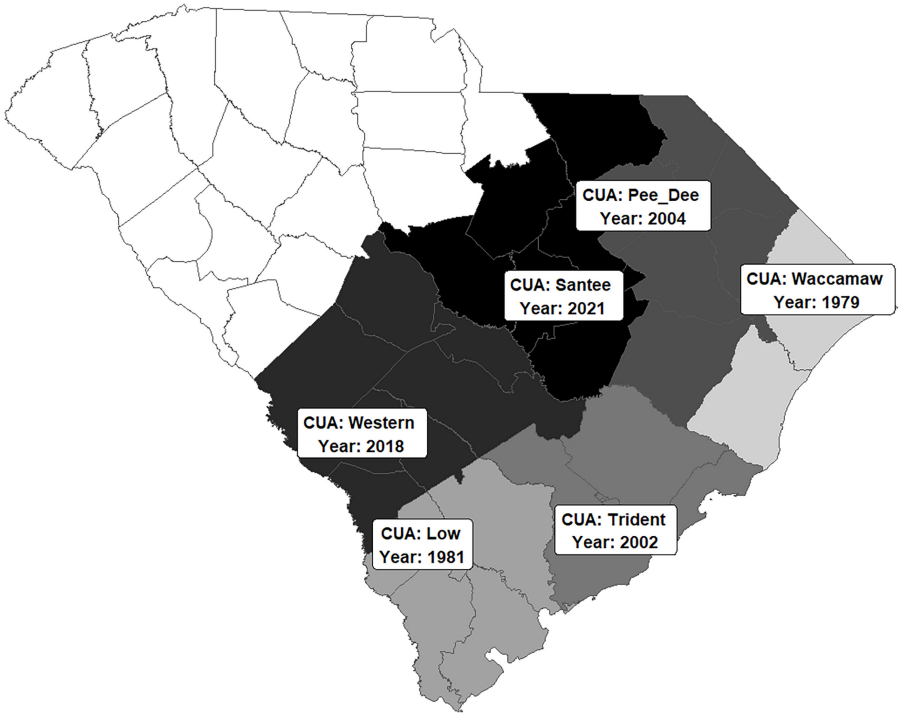


Figure 7. The capacity use areas (CUA) in South Carolina. Notes: The shading indicates the timing of CUA designations. Lighter shades represent the three earlier-designated CUAs (Waccamaw, Low, and Trident), located near the coastal regions. Darker shades correspond to the later-designated CUAs (Pee Dee, Western, and Santee Lynches).

designations of CUA were initiated around coastal counties (Figure 7). The first CUA created was Waccamaw (1979) followed by Lowcountry (1981 and expanded in 2008), Trident (2002), Pee Dee (2004), Western (2018), and finally, Santee Lynches (2021).

The location of the groundwater users determines if they need a permit to pump water for irrigation. Groundwater users who are located within a CUA are required to request a permit to construct and/or operate any well which will use over three million gallons in any one month (SCDES 2006).[2] Moreover, users outside CUAs need to register wells using over three million gallons per month. Statewide, all registered and permitted groundwater withdrawers must report their annual water use to the SCDES.[3]

Permits for usage are subject to review and renewal every 5 years, and wells must shut down if they are no longer serving a beneficial purpose (SCDES 2006). However, non-compliance with these regulations does not necessarily result in immediate permit or registration revocation. There is typically some flexibility in maintaining permit status, even if water withdrawal is below the claimed volumes.

[2]Three million gallons of water for one month amount to water to irrigate 12.28 acres of corn, 14.73 acres of soybeans, and 18.42 acres of peanuts or cotton, approximately. This calculation is based on daily evapotranspiration (ET) of around 0.3 inches/day for corn, 0.25 inches/day for soybeans, and 0.2 inches/day for peanuts and cotton. Small farms are likely to be excluded from 3MG rule.

[3]The term permits is used to refer to both permits and registrations.

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

Data

The data used for our estimation are drawn from several sources at the finest resolution possible. Irrigation adoption information is obtained from the SCDES's withdrawal data from 1983 to 2021. To evaluate new adoption, we use information on the first time a user reports withdrawals as a new permit is issued to that user.[4]

The initial dataset includes 1,003 permits and 3,034 wells registered for irrigation water use. After removing data without spatial information, we are left with 955 permits associated with 2,828 wells. The difference between the number of permits and wells indicates that some permits cover multiple wells. Furthermore, permits are not always uniquely identified because some farmers hold multiple permits. Multiple wells and permits can introduce bias in measuring peer effects, as multi-permits holders' decisions are not independent (Sampson and Perry 2019b). To avoid this issue, we create a unique match between each permit and well. As a result, our final dataset includes 451 permits with distinct corresponding well information. Detailed descriptions of our data processing methods for achieving unique permit identifications are provided in Supplementary Appendix A1. Lastly, in our sample, once a farmer adopts irrigation, they do not revert to dryland farming. We follow Sampson and Perry (2019b) to code the binary dependent variable after irrigation adoption, and, consequently, observations from years following the adoption of irrigation are excluded from the analysis.

We also identify the water amount associated with each unique permit by assigning representative water usage to each permit holder. Representative water usage refers to the amount of water associated with each representative well.[5] To calculate this, we aggregate the total water usage from all wells linked to a given permit for each year. In this way, the water amount assigned to a permit reflects usage from all wells under that permit, not just from the representative well. Similarly, when multiple permits are held by the same entity, we calculate the total water usage by aggregating across those permits. This approach enables us to assign a consistent and representative annual water usage value to each uniquely identified permit in our study.

We compile a variety of data that may influence irrigation adoption decisions, including weather conditions, soil characteristics and crop type. Table 1 presents the summary statistics for the key variables included in the empirical model.

Soil characteristics are obtained from the USDA NRCS (Natural Resources Conservation Service) gSSURGO dataset. We include the National Commodity Crop Productivity Index (NCCPI) and drought vulnerability index to examine the soil productivity factors. We also include other soil characteristics described next. Soil slope is defined as the difference in elevation between two points and reflects the degree of soil erosion. Soil clay content are determined by the particle sizes, which affect the degree of water-holding capacity. Eight drainage types define soil drainage data, from very poor to excellent drainage.[6]

[4]Our sample contains only farmers who eventually adopt irrigation during our study period. However, the data do not include information about farmers who never adopt but were also exposed to peer behavior. As a result, our estimates of peer effects may be biased upward since non-adopters – who might be less willing to adopt regardless of peer influence – are not accounted for.

[5]See Appendix A1 for the definition of representative wells.

[6]Drainage category 1 is very poor drainage, 2 is poor drainage, 3 is some poor drainage, 4 is not specified drainage, 5 is modestly well drainage, 6 is well drainage, 7 is some excellent drainage, and 8 is excellent drainage.

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

Table 1. Summary statistics

Variables	Unit	Mean	SD	Min	Max
Peer's irrigation adoption					
Peer irrigators (8km)	Number	3.86	3.42	0.00	20.00
Peer water use (8km)	Million gallons	247.55	508.13	0.00	3998.82
Drought data					
Abnormally dry† (D0)	Weeks	8.49	5.69	0.00	27.00
Moderate drought† (D1)	Weeks	4.46	5.96	0.00	29.00
Severe drought† (D2)	Weeks	1.52	3.23	0.00	17.00
Extreme/Exceptional drought† (D3 + D4)	Weeks	0.42	1.95	0.00	31.00
Soil property data					
National commodity crop productivity index	–	0.53	0.14	0.06	0.76
Soil drought index	–	0.25	0.23	0.00	0.89
Soil slope	–	2.08	1.74	0.68	11.00
Soil clay content	%	18.04	5.95	3.75	38.33
Soil drainage	Category	5.31	1.66	1.00	8.00
Crop types					
Corn binary	%	0.20	0.40	0.00	1.00
Cotton binary	%	0.15	0.35	0.00	1.00
Boundaries					
County	Number	25	–	–	–
Irrigation adoption					
Permits (2004–2021)	Number	451	–	–	–

Note: †indicates one-year lag variable.

Peer effects and identification concerns

The influence of peer irrigators on a farmer's decision to adopt irrigation can operate through two main distinct mechanisms: social interaction and social learning. Social interaction refers to situations in which an individual's utility from taking an action increases when others also take that action, regardless of whether information is exchanged or learning occurs (Cooper and Rege 2011; Lahno and Serra-Garcia 2015). For example, a farmer may install irrigation because his neighbors have done so, even without detailed information of the costs and benefits. In contrast, social learning occurs when individuals acquire information about the value and effectiveness of an action by observing the behavior and outcomes experienced by others (Banerjee 1992; Cooper and Rege 2011). In this case, a farmer may need to receive information that irrigation has improved neighbors' crop yields or reduced production risks before deciding to adopt similar practices.

We assume that the benefits of adopting irrigation are uncertain for farmers prior to adoption. Farmers may form prior beliefs about these potential benefits based on

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

observable factors related to irrigation installation. These beliefs can then be updated through opportunities to learn from peers who have already adopted irrigation (Genius et al. 2014; Moretti 2011). Such belief updating primarily occurs through social learning, as farmers receive feedback – either directly or through observation – from neighboring adopters. We argue that in regions like the Eastern U.S., where irrigation serves as a supplemental input, peer effects on irrigation adoption may operate not only through social interaction but also, and perhaps more importantly, through social learning. The potential for social learning may be further enhanced during drought conditions, when the value of irrigation becomes even more apparent. In such periods of water stress, farmers are more likely to observe and internalize the advantages of irrigation, increasing the likelihood of adoption.

There are several challenges common to empirical analysis of social mechanisms. The first one refers to the definition of the peer group. The SCDES withdrawal data provide information about the water permit's location, but no information about who their peers are is available. We combine the location and irrigation adoption information to define the adopter's peer network based on geography (Bollinger et al. 2020; Sampson and Perry 2019a) rather than spatial proximity (Sampson and Perry 2019b; Towe and Lawley 2013). The intuition behind this definition is that irrigation systems are visible to peers so farmers are more likely to be exposed to information about irrigation practices when they are nearby. Additionally, farms in South Carolina differ in field sizes and the distances between them. Consequently, using spatial proximity (e.g., the nearest 13 neighbors) to define peer groups may be problematic if the selected farms are not sufficiently close to one other to provide meaningful information about irrigation practices.

We create a buffer around each water permit to define peer group as farmers who eventually adopt irrigation within a 8-km radius of each individual farmer in our dataset. To address uncertainty regarding the distance farmers consider relevant for peer influence, we vary buffer sizes from 3 to 20 km as part of our robustness check in Section (*Robustness checks*). A graphical illustration of a buffer used to compute the installed base is provided in figure A3, Supplementary Appendix, section A2. However, this definition of peer group does not account for other social interactions that occur outside the buffer. For instance, farmers may interact with peers in cooperatives, extension centers, or input stores. Therefore, our definition of a peer group can be considered as the minimum threshold for social interaction that influences irrigation adoption decisions.

There are two main types of effects that explain why members of the same group could behave similarly (Bollinger and Gillingham 2012; Manski 1993b). The first is contextual effects, which occur when the behavior of individuals in a group is influenced by exogenous characteristics of the group. In our context, there is an exogenous effect if farmers' irrigation adoption decisions vary with soil characteristics, weather, or crop choices. In contrast, endogenous effects (i.e., peer effects) occur when an individual's behavior is directly influenced by the actions of other group members (Burlig and Stevens 2023; Di Falco et al. 2020). An example of an endogenous effect is if a farmer's decision to adopt irrigation is influenced by exchanging information about the returns to irrigation with their peers.

From a policy perspective, it is important to disentangle endogenous peer effects from contextual effects due to different policy implications (Manski 1993b). However, there are three common sources of endogeneity that make the identification of peer effects challenging (Bollinger and Gillingham 2012; Manski 1993b): self-selection of peer group, correlated unobservables, and simultaneity (i.e., reflection). The first is self-selection of the peer group (i.e., homophily), which can occur when individuals can choose their peer group. In our context, farmers with similar preferences may sort into a certain rural area,

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

or more progressive farmers might form a group where everyone is inclined towards adopting new technologies. Thus, this self-selection can bias the estimation of peer effects because the decision to adopt irrigation is not only due to peer influence but also to pre-existing similarities.

Various contextual factors, such as soil characteristics, crop type, and weather could influence irrigation adoption. We control for these factors by including a rich set of covariates. However, many other factors (e.g., farmers' preferences, policy changes, macroeconomic shocks) may affect both individual farmers and peers but are unobserved by the researcher. Failing to control these unobserved factors makes isolating the actual peer effect difficult, leading to the second source of endogeneity, correlated unobservables.

A common approach to addressing the self-selection of peers and correlated unobservables is to include random or fixed effects (Bollinger and Gillingham 2012; Nair et al. 2010; Sampson and Perry 2019a). We include several fixed effects to account for unobserved heterogeneity. Year fixed effects are included to control for time-varying unobserved factors, while county fixed effects account for time-invariant spatial differences across counties. Lastly, we further control for unobserved largely spread shocks, especially spatial-temporal shocks by using the common correlated effect (CCE) at the state level as suggested by Sampson and Perry (2019b). The CCE is defined as $\sum_i d_{it}/I_t$, a ratio between d_{it} (1 if i adopts irrigation in time t) and I_t (the number of eventual adopters in time t that have not yet adopted. Thus, CCE aims to control for unexpected adoption patterns at the state levels.

The last identification concern relates to the simultaneity or reflection problem, which occurs when the decision of one farmer to adopt irrigation might influence, and be influenced by, the decisions of their peers simultaneously. The reflection problem creates a challenge in distinguishing whether a farmer's decision is influencing their peers or vice versa. This issue is common when estimating peer effects using observational data and can introduce bias if not addressed (Bollinger and Gillingham 2012; Manski 1993a). Similar to previous studies (Sampson and Perry 2019b; Sampson and Perry 2019a), we expect a low impact from the reflection problem due to the lag between when a farmer observes their peers obtaining a positive return from irrigation and when he decides to install irrigation. Thus, we follow the approach proposed by Bollinger and Gillingham (2012) to define installed base as the variable measuring peer effects. The installed base is the cumulative number of adopters up to the previous calendar year within a peer group. We calculate the installed base using the following formula:

$$b_{z_i t} = \sum_{\tau=1}^{t-1} \sum_{j=1}^{m_{z_i}} a_{j\tau}. \tag{1}$$

where m_{z_i} is the number of farmers within the peer group who eventually adopt, and $a_{j\tau}$ is an indicator variable of adoption in year τ. The installed base of farmer i in peer-group z in year t (i.e., $b_{z_i t}$) reflects the stock of neighbors that have adopted irrigation at or before $(t-1)$.

Empirical model

This section describes the empirical model to estimate the peer effects on irrigation adoption. We observe each farmer i over $t = 1, \ldots, T_i$ years, where T_i represents the year in which farmer i decides to adopt irrigation $(y_{it} = 1)$. We assume that the adoption

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

decision is based on a comparison of the anticipated profits from adopting irrigation, $\pi_{it}(y_{it}=1)$, with the profits from not adopting, $\pi_{it}(y_{it}=0)$. Thus, farmer i chooses to adopt irrigation in year t if $\pi_{it}(y_{it}=1) > \pi_{it}(y_{it}=0)$.

The profit function can be decomposed into two components – an observed part V_{it}, and unobserved error term ε_{it}:

$$\pi_{it} = V_{it} + \varepsilon_{it} \tag{2}$$

The observed part is further modeled as a function of the installed base, defined in Equation 1, as well as production-related characteristics:

$$V_{it} = \beta_1 Peer_{i,t-1} + \beta_2 Peer_{i,t-1}^2 + \gamma' X_{i,t-1} + \Psi' CCE_t + \Phi' Z_i + \eta_t + \mu_g, \tag{3}$$

where $Peer_{i,t-1}$ denotes either the number of neighboring farmers who had adopted irrigation by year $t-1$ (i.e., installed base of farmer i in year t), or the amount of irrigation water used by those neighboring farmers who had adopted irrigation by year $t-1$.[7] We employ these two distinct measures of peer effects to explore the plausibility of the two potential mechanisms, social interaction and social learning, without attempting to compare their relative magnitudes. We use peers' water use as a measure to the potential knowledge gains provided to those peers that are irrigating. To capture potential non-linearities in peer effects, we include the squared term of the peer variable $Peer_{i,t-1}$. $X_{i,t-1}$ represents a vector of time-varying drought conditions – measured as the number of weeks under each drought severity level (D0, D1, D2, and D3 + D4) at the location of individual irrigators in year $t-1$. CCE_t represents common correlated effects at the state level. Z_i contains time-invariant variables such as soil characteristics. η_t and μ_g are temporal and spatial fixed effects. β_1, β_2, γ, Ψ, Φ indicate the parameters to be estimated.

The probability of adopting irrigation can be estimated using a logit model within the random utility framework. Assuming that unobservable component ε_{it}, in Equation 3, is IID and follows the Type I extreme value distribution, the probability of adopting irrigation is given by the logit expression:

$$Pr(y_{it}=1|V_{it}) = \Lambda[V_{it}] = \frac{exp(V_{it})}{1+exp(V_{it})} \tag{4}$$

where Λ represents the logistic cumulative distribution function, which ensures that the probability lies within the range of 0 to 1. Equation 4 can be expressed in terms of the odds of adoption as $\frac{Pr(y_{it}=1)}{(1-Pr(y_{it}=1))} = exp(V_{it})$.

Our primary goal is to estimate how changes in covariates affect the probability of irrigation adoption. To achieve this, we can estimate either the odds ratio (OR) or the marginal effects (ME). The odds ratio represents the ratio of the odds of irrigation adoption when a j^{th} covariate (X_j) is increased by one unit, and is expressed as $\theta = \frac{exp(V_{it}(X_j+1))}{exp(V_{it}(X_j))}$. When V_{it} is linear in the covariates, the odds ratio simplifies to $exp(\beta_j)$. We use marginal effects to test peer effects, as they are easier to interpret in a

[7]As noted in Section (*Data*), observations after a farmer adopts irrigation are excluded. However, the installed base for each observation is calculated using the entire dataset. This approach ensures that the $Peer_{it}$ variable incorporates comprehensive information about neighboring irrigators.

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

non-linear logistic regression model. To estimate the marginal effect of the *Peer* variable in our specification, we use the following expression:

$$\frac{\partial Pr(y_{it}=1)}{\partial Peer_{i,t-1}} = \Lambda'[V_{it}] \cdot \frac{\partial V_{it}}{\partial Peer_{i,t-1}}$$

The Average Marginal Effect (AME) is computed by first calculating the marginal effect for each observation in the sample, using the observed values of all covariates. The individual marginal effects are then averaged, providing a summary measure of the overall impact.

The odds ratio can be interpreted as the odds of adopting irrigation change with a one-unit increase in a variable. Thus, an odds ratio greater than one indicates the increasing likelihood of adoption, while less than one suggests a decreasing likelihood. In contrast, the AME measure the marginal change in the probability of adoption for each unit increase in a covariate, offering a direct interpretation of how covariates affect adoption probability.

Results

Table 2 presents the estimation results from the logistic regression. The table presents two columns corresponding to alternative model specifications of peer effect mechanisms. Column (1) uses *Peer*, the number of peer irrigators (i.e., the installed base), as the main explanatory variable – primarily capturing the social interaction mechanism. In contrast, column (2) uses peers' water use as the key explanatory variable to capture the information channel through which social learning occurs. *Peer Water Use* is calculated as the sum of irrigation water used by the installed-base peers in the previous years. As such, the *Peer Water Use* reflects not only the number of peers but also their pumping behavior, which is likely influenced by annual weather conditions as farmers adjust irrigation to maximize crop revenue. Therefore, *Peer Water Use* captures the value of irrigation among peers in a given year, as observed by a given farmer – social learning mechanism.

We estimate two alternative specifications that separately capture social interaction (number of adopting peers) and social learning (peers' water use). It is important to note that these specifications are not intended to determine which peer-effect mechanism dominates, because the peer variables are measured on different scales and their coefficients are not directly comparable across models. All models include year fixed effects and county fixed effects. Standard errors are clustered at the county level to account for heteroskedasticity and spatial correlation in unobserved errors. All peer variables are constructed based on the installed base within an 8 km radius buffer.

Our results in Column (1) of Table 2 show evidence of peer effects operating through the social interaction mechanism on irrigation adoption among farmers who adopt irrigation. Specifically, the estimated coefficients for Peer, along with the corresponding marginal effects, are positive and statistically significant. That is, one more peer irrigator increases the probability of irrigation adoption by about 0.4 percentage point. In addition, Column (2) provides some evidence of peer influence under conditions that enhance opportunities for learning about the value of irrigation. For instance, such opportunities are likely to be enhanced during drought conditions, when increased pumping by peers makes the benefits of irrigation more observable. Specifically, a 100 million gallon increase in peer irrigation water use is associated with a 0.3 percentage point increase in the probability of adoption. In both columns, the squared term of Peer is less than one, suggesting some evidence of diminishing peer effects. However, the estimates are not statistically significant.

We also report odds ratios in Table 2 to examine additional factors influencing irrigation adoption. In both columns, the odds ratios for milder droughts (D0–D2) are less

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

Table 2. Estimation results from logistic regression models

	(1)	(2)
Odds ratio		
Peer (# of irrigators)	1.1400**	
	(0.0696)	
Peer squared (# of irrigators)	0.9940	
	(0.0041)	
Peer (Water quantity, Mil. Gal)		1.0006**
		(0.0003)
Peer squared (Water quantity, Mil. Gal)		0.9999
		(0.0000)
Drought D0 (# of weeks)	0.9792	0.9812
	(0.0199)	(0.0195)
Drought D1 (# of weeks)	0.9908	0.9933
	(0.0353)	(0.0350)
Drought D2 (# of weeks)	0.9006***	0.9009***
	(0.0326)	(0.0322)
Drought D3 + D4 (# of weeks)	1.0633	1.0676
	(0.0468)	(0.0464)
Soil productivity (NCCPI)	0.8875	1.0954
	(0.5120)	(0.6039)
Soil drought index	1.0316	1.0888
	(0.6171)	(0.6168)
Soil slope	1.0808**	1.0791**
	(0.0418)	(0.0385)
Soil clay content	1.0302**	1.0294**
	(0.0126)	(0.0130)
Drainage category	1.0129	1.0054
	(0.0945)	(0.0928)
CCE (State)	1.1619***	1.1598***
	(0.0362)	(0.0366)
Average marginal effects		
Peer effects	0.0040186**	0.0000280**
(*p*-value)	(0.012)	(0.023)
Year fixed effect	Yes	Yes
County fixed effect	Yes	Yes

(*Continued*)

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

Table 2. (*Continued*)

	(1)	(2)
N	5526	5526
pseudo R^2	0.259	0.258
Log-pseudolikelihood	−1110.2426	−1111.759

Notes: Odds ratios reported; standard errors in parentheses. Standard errors clustered by county. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Year and county fixed effects are included in all models. Drought variables are lagged by one year.

than one, although only drought at the D2 level is statistically significant. This suggests that each additional week of drought at the D2 level in the previous year reduces the odds of irrigation adoption by about 10%. One possible explanation is that farmers may respond to moderate droughts by temporarily reducing crop acreage to limit production risks rather than investing in new irrigation systems. By contrast, under more severe droughts (D3–D4), the odds ratio exceeds one, indicating that farmers may be more likely to consider adoption during extreme or exceptional droughts. However, these effects are not statistically significant. Soil characteristics appear to play a role. For instance, steeper slopes are associated with greater odds of adopting irrigation – 7.9–8.1% increase in odds. Moreover, a 1% increase in clay content raises the odds of adoption by 2.9–3.0%.[8]

Robustness checks

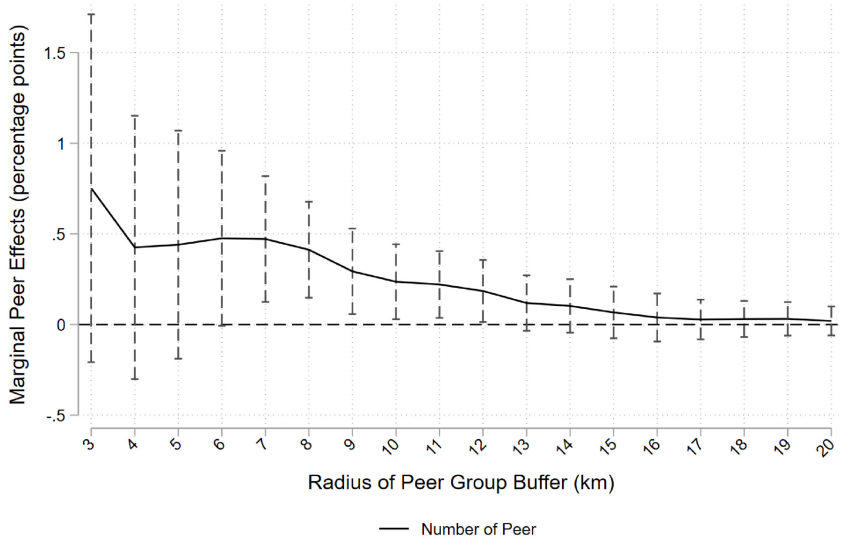
We conduct two robustness checks to assess the sensitivity of the estimation results. First, we estimate linear probability models as an alternative to logit models. In logistic regression, the estimation of marginal effects incorporates all parameters, which can result in biased estimates when multiple fixed effects are included – a phenomenon known as incidental parameters bias (Greene et al. 2002). To address this issue, we employ Ordinary Least Squares (OLS) regression using the same four model specifications as in Table 2.

The OLS regression results are presented in table A4 in Supplementary Appendix section A5. Consistent with the logistic regression results in Table 2, the average marginal peer effects in the OLS models are statistically significant in columns (1) and (2).

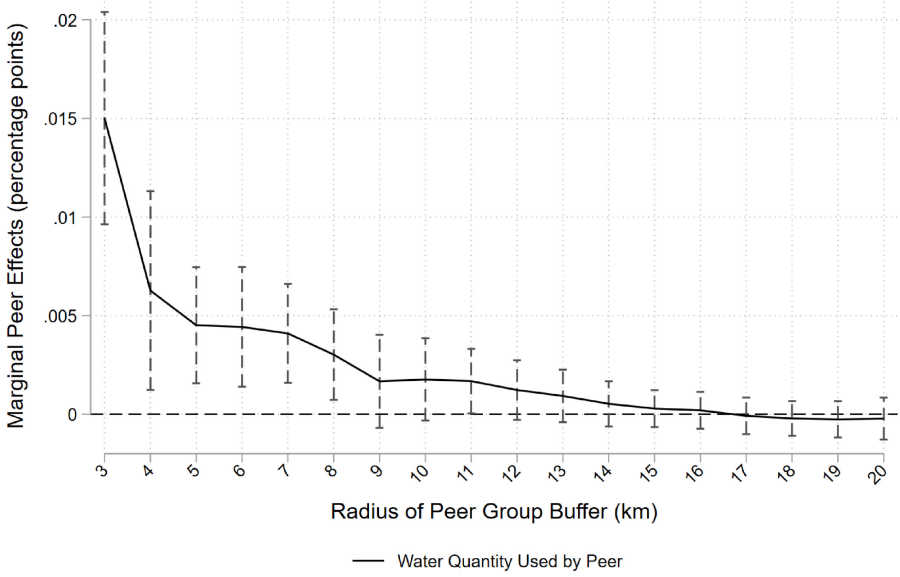
Our second robustness check examines whether estimates from our main model specification (using an 8 km radius definition of peer group) are sensitive to changes in peer group size. Figure 8 presents the estimated average marginal effects of the number of irrigators and peers' water use in panels A and B, respectively. Each panel shows the average marginal peer effects for peer group sizes ranging from 3 km to 20 km. The results indicate that as the peer group size increases, the impact of peer effects generally diminishes across both mechanisms. However, the positive and statistically significant peer effect associated with peer numbers remains robust for most radii between 7 km and 11 km, while the peer effect associated with peer water use remains robust for most radii between 3 km and 8 km. Overall, these findings suggest that the peer effect remains generally consistent across varying peer group sizes.

[8]Our preferred specifications in Table 2 do not include crop information from the CDL data, allowing us to use a longer time series. However, table A3 in Supplementary Appendix section A4 shows that crop type significantly influences irrigation decisions. In particular, growing corn increases the odds of adopting irrigation by 65%, consistent with expectations, as corn is a high-value, water-intensive crop that benefits substantially from reliable water availability.

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press



Panel A: Marginal Peer Effect by Number of Peer



Panel B: Marginal Peer Effect by Peer Water Quantity

Figure 8. Marginal Peer Effects by Peer Group Size. **Panel A** plots the estimated marginal effects of peer irrigation adoption (number of irrigators) for each peer group size, ranging from 3 km to 20 km. **Panel B** plots the estimated marginal effects of peer water use (water quantity) for each peer group size, ranging from 3 km to 20 km.

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

Discussion and conclusions

Agriculture is one of the sectors most vulnerable to climate change, with rising temperatures already leading to reduced crop yields (Lobell et al. 2011; Ortiz-Bobea et al. 2021; Tack et al. 2015). Irrigation adoption is often suggested as a potential adaptation practice to mitigate the risks associated with drought conditions, and expanding irrigation across rain-fed croplands could help to meet future global food demand (Rosa 2022). In the U.S., irrigated areas are increasing in the Midwest, the Mississippi Alluvial Plain, and the East Coast, while decreasing in hotspots such as the central and southern High Plains, southern Central Valley in California and Arizona (Xie and Lark 2021), where irrigation has played a key role in the development of agriculture (Edwards and Smith 2018; Hornbeck and Keskin 2014).

Despite the potential for sustainable irrigation expansion in the eastern U.S. (Mehta et al. 2024; Rosa et al. 2020), adoption rates remain low (Cooley and Smith 2022). For example, irrigated corn acres in South Carolina were 18% in 2022 – well below rates in Georgia (52%) and Florida (45%) (USDA 2025). In this context, understanding whether a farmer's decision to adopt irrigation is influenced by the irrigation practices of their peers could improve the effectiveness of policies aimed at mitigating drought risks.

We find evidence that both a greater number of peer irrigators and higher water use by peers influence adoption decisions among farmers who adopt irrigation. Our results suggest that adoption increases as farmers observe more peer adopting irrigation – social interactions – and as peers' pumping increases, such as during drought periods, when the benefits of irrigation become more visible and there are more opportunities to observe and learn the value of irrigation, facilitating social learning.

The evidence of peer effects presented in our paper aligns with the results reported among farmers in Kansas by Sampson and Perry (2019b), who found peer effects of 0.25–0.41 percentage points depending on model specifications. This consistency between the two studies highlights the important role of peer influence through social interaction, despite several key contextual differences. Moreover, our study complements these previous results by providing evidence of the additional role of peer effects operating through social learning.

In Kansas, crop production relies heavily on groundwater irrigation as the primary source of water, whereas crop production in South Carolina depends predominantly on rainfall. Farmers in South Carolina receive nearly twice the annual rainfall of their counterparts in Kansas, with an average precipitation of 787 mm in South Carolina compared to 416 mm in Kansas. Therefore, irrigation in South Carolina primarily serves as a supplement to rainfall, rather than being a consistent, year-to-year source of water, which may offer minimal or no net economic benefit (Partridge et al. 2023). However, our results are consistent with Sampson and Perry (2019b), indicating that peer effects – measured by neighboring irrigators – are also an important driver of irrigation adoption in South Carolina.

Groundwater depletion–combined with the common-pool nature of the resource–can influence irrigation adoption decisions, as farmers may be concerned about overuse by their peers Sampson and Perry (2019b). When groundwater is perceived as a common-pool resource, farmers may anticipate that their neighbors' adoption of irrigation will accelerate depletion, prompting them to adopt sooner in order to secure access. This type of strategic behavior is more prevalent in regions like Kansas, where groundwater resources are being rapidly depleted. In contrast, such concerns are less pronounced in South Carolina, where groundwater remains relatively abundant, and aquifer depletion is not yet a significant issue. In South Carolina, by contrast, farmers are more likely to be influenced not only by peers

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

adopting irrigation but also by social learning – requiring clear evidence of benefits such as improved yields or reduced production risks before choosing to adopt.

Another key difference is that Kansas farmers face less uncertainty about the benefits of irrigation, given the state's long history using irrigation. In contrast, irrigation remains relatively new in South Carolina. In addition, the high upfront costs associated with installing irrigation equipment can limit economic returns from irrigation (Caswell and Zilberman 1986). These factors may reduce farmers' incentives to adopt irrigation. However, observing and learning from neighboring irrigators can reduce this uncertainty, creating additional incentives for adoption through social learning mechanisms.

Our results provide important insights for policymakers aiming to expand irrigated agriculture as a strategy to mitigate drought-related risks. In future scenarios characterized by more frequent and severe droughts (Strzepek et al. 2010), government programs that provide technical and financial assistance for irrigation adoption could generate positive spillover effects benefiting not only direct participants but also influencing neighboring farmers through peer-based learning. Drought conditions, in particular, can enhance opportunities for social learning, as the benefits of irrigation become more visible through peers' drought management responses.

An important limitation of our study is that the sample includes only farmers who eventually adopt irrigation during the study period. The data do not capture information on farmers who never adopt, despite potentially being exposed to peer behavior. As a result, our estimates of peer effects may be biased upward, since non-adopters – who may be less inclined to adopt regardless of peer influence – are not included in the analysis. This type of sample selection issue is common in the peer effects literature, particularly in studies relying on adoption data that exclude non-adopters (Sampson and Perry 2019b). Consequently, our findings specifically address whether peer effect influences the likelihood of adoption among farmers who adopt irrigation, rather than capturing the broader effect of peer influence on adoption decisions across the entire farming population, including non-adopters.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/age.2025.10017

Data availability statement. The data that support the findings of this study are available from the authors upon request.

Funding statement. This work was partially supported by the Research Capacity Fund (Hatch) from the U.S. Department of Agriculture (SC-1700676).

Competing interests. The authors declare no competing interests.

References

Akyuz FA (2017) Drought severity and coverage index. Available at https://droughtmonitor.unl.edu/About/AbouttheData/DSCI.aspx. United States Drought Monitor.

Banerjee AV (1992) A simple model of herd behavior. *The Quarterly Journal of Economics* **107**, 797–817.

Bollinger B, Burkhardt J and Gillingham KT (2020) Peer effects in residential water conservation: Evidence from migration. *American Economic Journal: Economic Policy* **12**, 107–133.

Bollinger B and Gillingham K (2012) Peer effects in the diffusion of solar photovoltaic panels. *Marketing Science* **31**, 900–912.

Burlig F and Stevens AW (2023) Social networks and technology adoption: Evidence from church mergers in the US midwest. *American Journal of Agricultural Economics* **106**, 1141–1166.

Campbell B, Petkewich M, Coes A and Fine J (2012) Ground-water availability in the Atlantic Coastal Plain of North and South Carolina.

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

Carey JM and Zilberman D (2002) A model of investment under uncertainty: Modern irrigation technology and emerging markets in water. *American Journal of Agricultural Economics* **84**, 171–183.

Caswell MF and Zilberman D (1986) The effects of well depth and land quality on the choice of irrigation technology. *American Journal of Agricultural Economics* **68**, 798–811.

Che Y, Feng H and Hennessy DA (2022) Assessing peer effects and subsidy impacts in conservation technology adoption: Application to grazing management choices. *Journal of the Agricultural and Applied Economics Association* **1**, 285–303.

Cooley DJ and Smith SM (2022) Center pivot irrigation systems as a form of drought risk mitigation in humid regions. Technical report, National Bureau of Economic Research.

Cooper DJ and Rege M (2011) Misery loves company: Social regret and social interaction effects in choices under risk and uncertainty. *Games and Economic Behavior* **73**, 91–110.

Deines JM, Schipanski ME, Golden B, Zipper SC, Nozari S, Rottler C, Guerrero B and Sharda V (2020) Transitions from irrigated to dryland agriculture in the Ogallala aquifer: Land use suitability and regional economic impacts. *Agricultural Water Management* **233**, 106061.

Di Falco S, Doku A and Mahajan A (2020) Peer effects and the choice of adaptation strategies. *Agricultural Economics* **51**, 17–30.

Edwards EC and Smith SM (2018) The role of irrigation in the development of agriculture in the united states. *The Journal of Economic History* **78**, 1103–1141.

Erev I and Roth AE (2014) Maximization, learning, and economic behavior. *Proceedings of the National Academy of Sciences* **111**, 10818–10825.

Foster AD and Rosenzweig MR (1995) Learning by doing and learning from others: Human capital and technical change in agriculture. *Journal of political Economy* **103**, 1176–1209.

Gellici J (2011) Updating the South Carolina Water Plan. SC Department of Natural Resources. Available at https://dc.statelibrary.sc.gov/server/api/core/bitstreams/12239fa6-953e-4c70-b2c5-7b2fe34d2ec9/content (accessed 14 April 2024).

Genius M, Koundouri P, Nauges C and Tzouvelekas V (2014) Information transmission in irrigation technology adoption and diffusion: Social learning, extension services, and spatial effects. *American Journal of Agricultural Economics* **96**, 328–344.

Greene W, Han C and Schmidt P (2002) The bias of the fixed effects estimator in nonlinear models. *Unpublished Manuscript, Stern School of Business, NYU* **29**, 2002.

Hendricks NP and Peterson JM (2012) Fixed effects estimation of the intensive and extensive margins of irrigation water demand. *Journal of Agricultural and Resource Economics* **37**, 1–19.

Hornbeck R and Keskin P (2014) The historically evolving impact of the Ogallala aquifer: Agricultural adaptation to groundwater and drought. *American Economic Journal: Applied Economics* **6**, 190–219.

Hrozencik A and Aillery M (2022) Trends in irrigated agriculture reveal sector's ability to adapt to evolving climatic, resource, and market conditions. *Amber Waves: The Economics of Food, Farming, Natural Resources, and Rural America* **2022**, 1490-2022-276.

Lahno AM and Serra-Garcia M (2015) Peer effects in risk taking: Envy or conformity?. *Journal of Risk and Uncertainty* **50**, 73–95.

Lobell DB, Schlenker W and Costa-Roberts J (2011) Climate trends and global crop production since 1980. *Science* **333**, 616–620.

Manski CF (1993a) Adolescent econometricians: How do youth infer the returns to schooling?. In Clotfelter CT and Rothschild M (eds). *Studies of Supply and Demand in Higher Education*. Chicago, IL: University of Chicago Press, pp. 43–60.

Manski CF (1993b) Identification of endogenous social effects: The reflection problem. *The review of economic studies* **60**, 531–542.

Martínez DM, Maia AG and Garcia JR (2022) Spatial diffusion of efficient irrigation systems: A study of são paulo, Brazil. *Australian Journal of Agricultural and Resource Economics* **66**, 690–712.

Mehta P, Siebert S, Kummu M, Deng Q, Ali T, Marston L, Xie W and Davis KF (2024) Half of twenty-first century global irrigation expansion has been in water-stressed regions. *Nature Water* **2**, 254–261.

Moretti E (2011) Social learning and peer effects in consumption: Evidence from movie sales. *The Review of Economic Studies* **78**, 356–393.

Mrad A, Katul GG, Levia DF, Guswa AJ, Boyer EW, Bruen M, Carlyle-Moses DE, Coyte R, Creed IF, Van De Giesen N, Grasso D, Hannah DM, Hudson JE, Humphrey V, Iida S, Jackson RB, Kumagai T, Llorens P, Michalzik B, Nanko K, Peters CA, Selker JS, Tetzlaff D, Zalewski M and Scanlon BR (2020)

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press

Peak grain forecasts for the us high plains amid withering waters. *Proceedings of the National Academy of Sciences* **117**, 26145–26150.

Mullen JD, Yu Y and Hoogenboom G (2009) Estimating the demand for irrigation water in a humid climate: A case study from the southeastern united states. *Agricultural Water Management* **96**, 1421–1428.

Nair HS, Manchanda P and Bhatia T (2010) Asymmetric social interactions in physician prescription behavior: The role of opinion leaders. *Journal of Marketing Research* **47**, 883–895.

Nix H and Rad MR (2022) *Water Withdrawal Regulation in South Carolina*. Clemson, SC: Land-Grant Press.

Ortiz-Bobea A, Ault TR, Carrillo CM, Chambers RG and Lobell DB (2021) Anthropogenic climate change has slowed global agricultural productivity growth. *Nature Climate Change* **11**, 306–312.

Partridge T, Winter J, Kendall A, Basso B, Pei L and Hyndman D (2023). Irrigation benefits outweigh costs in more us croplands by mid-century. *Communications Earth & Environment* **4**, 274.

Perry ED, Hennessy DA and Moschini G (2022) Uncertainty and learning in a technologically dynamic industry: Seed density in us maize. *American Journal of Agricultural Economics* **104**, 1388–1410.

Reidmiller DR, Avery CW, Easterling DR, Kunkel KE, Lewis KL, Maycock TK and Stewart BC (2017) Impacts, risks, and adaptation in the united states: Fourth national climate assessment, volume ii.

Rosa L (2022) Adapting agriculture to climate change via sustainable irrigation: Biophysical potentials and feedbacks. *Environmental Research Letters* **17**, 063008.

Rosa L, Chiarelli DD, Sangiorgio M, Beltran-Peña AA, Rulli MC, D'Odorico P and Fung I (2020) Potential for sustainable irrigation expansion in a 3 c warmer climate. *Proceedings of the National Academy of Sciences* **117**, 29526–29534.

Sampson GS and Perry ED (2019a) Peer effects in the diffusion of water-saving agricultural technologies. *Agricultural Economics* **50**, 693–706.

Sampson GS and Perry ED (2019b) The role of peer effects in natural resource appropriation–The case of groundwater. *American Journal of Agricultural Economics* **101**, 154–171.

SCDES (2006) Regulation 61-113. Groundwater Use and Reporting (accessed 14 April 2024).

Schoengold K, Sunding DL and Moreno G (2006) Price elasticity reconsidered: Panel estimation of an agricultural water demand function. *Water resources research* **42**, W09411 (1–10).

Smith SM, Andersson K, Cody KC, Cox M and Ficklin D (2017) Responding to a groundwater crisis: The effects of self-imposed economic incentives. *Journal of the Association of Environmental and Resource Economists* **4**, 985–1023.

Smith SM and Edwards EC (2021) Water storage and agricultural resilience to drought: Historical evidence of the capacity and institutional limits in the United States. *Environmental Research Letters* **16**, 124020.

Strzepek K, Yohe G, Neumann J and Boehlert B (2010) Characterizing changes in drought risk for the United States from climate change. *Environmental Research Letters* **5**, 044012.

Tack J, Barkley A and Hendricks N (2017) Irrigation offsets wheat yield reductions from warming temperatures. *Environmental Research Letters* **12**, 114027.

Tack J, Barkley A and Nalley LL (2015) Effect of warming temperatures on us wheat yields. *Proceedings of the National Academy of Sciences* **112**, 6931–6936.

Taylor MM (2018) Brief overview of south carolina water law [powerpoint presentation]. Presented at: State Water Planning Process Advisory Committee Meeting, Columbia, SC.

Towe C and Lawley C (2013). The contagion effect of neighboring foreclosures. *American Economic Journal: Economic Policy* **5**, 313–335.

Troy TJ, Kipgen C and Pal I (2015) The impact of climate extremes and irrigation on us crop yields. *Environmental Research Letters* **10**, 054013.

USDA (2025) National Agricultural Statistics Service (accessed 6 June 2025).

Wachob A, Park A and Newcome JR (2009) South Carolina state water assessment. SC Department of Natural Resources. Land, Water and Conservation Division. Available at https://www.dnr.sc.gov/water/hydro/HydroPubs/assessment/SC_Water_Assessment_2.pdf (accessed 14 April 2024).

Xie Y and Lark TJ (2021) Mapping annual irrigation from landsat imagery and environmental variables across the conterminous United States. *Remote Sensing of Environment* **260**, 112445.

Cite this article: Jeong, D. and G. Perez-Quesada (2026). "Peer effects in irrigation adoption in South Carolina." *Agricultural and Resource Economics Review* **55**, 124–144. https://doi.org/10.1017/age.2025.10017

https://doi.org/10.1017/age.2025.10017 Published online by Cambridge University Press