Estimation of Property Value Changes from Nearby Carbon Capture, Utilization, and Storage Projects in the United States

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Abstract

Carbon capture, utilization, and storage (CCUS) techniques are vital to reaching decarbonization goals. Using nationwide CCUS data and property-level housing transaction records in the U.S., we quantify the impact of CCUS projects on nearby property values. Our research reveals three main findings. First, within 15 km of a CCUS project, property values decrease by 10.18% on average and the impact is heterogeneous depending on the property proximity. Second, a CCUS project's negative impact varies across the project types and facility conditions. The value of a property decreases by 9.88% and 6.42% after a carbon capture-only and a carbon storage-only project is operational within 15 km of the property, respectively. Retrofit CCUS facilities have no significant impact on nearby housing prices, whereas new-built CCUS facilities significantly reduce nearby house prices by 10.68%. Third, we apply a DDD approach to distinguish between CCUS effects and oil basin effects on housing prices and find that the CCUS operation has a net impact of -17.84% on nearby housing prices when compared to similar houses in oil basins without CCUS operations. Our mechanism analysis indicates that the increase in house prices resulting from CCUS within 5 km may be attributed to the implementation of CCUS projects which capture carbon emissions and improve local air quality. Reduced house prices within 15 km of CCUS projects may be attributed to a decrease in both local economic development and air quality. We also explore the heterogeneous responses of CCUS operations based on environmental awareness, local economic activities, and the facility industry. Our paper provides important policy implications on the local economic impacts and the siting choices of CCUS projects. The study provides useful insights into how CCUS projects may be expanded efficiently.

Keywords: CCUS; carbon capture; carbon storage; housing prices

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1 Introduction

The carbon capture, utilization, and storage (CCUS) technique is widely recognized as an irreplaceable negative emission technology, which is of great significance in combating climate warming (Smith et al., 2015; Davis et al., 2018; Duan et al., 2021). The CCUS technology is expected to provide 15% of the cumulative emission reduction contribution in the 2070 sustainable development scenario (IEA, 2020). As of Jan 2022, there were 38 CCUS projects that were completed, in operation, or operation in suspension in the U.S. Despite the rapid development of CCUS projects, the economic costs and benefits of CCUS projects in local communities are rarely assessed quantitatively, which presents great challenges to relevant policy decisions regarding CCUS project expansions.

The environmental and economic benefits of CCUS projects are multifold. While the benefits of carbon sequestration are accrued at a global level, the potential negative externalities of CCUS projects are mostly borne by local communities. A CCUS project, for example, may pose a risk to nearby geological formations, and thus increase the risk of complications such as earthquakes (Zoback & Gorelick, 2012, 2015). CO_2 that has been liquefied or stored under high pressure may lead to groundwater contamination when leaks occur during the process of geologic sequestration, resulting in the mobilization of hazardous inorganic elements during this process (Eldardiry & Habib, 2018). Water pollution may also be caused by the displacement of brine in the environment (Newmark et al., 2010). It has been suggested that the energy penalty issue associated with CCUS in power plants may lead to increased air pollution (EEA, 2011; Jacobson, 2019). It is difficult to accurately quantify these geological and pollution risks and the impact of such risks on local communities due to the lack of data and causal evidence. Nonetheless, it is believed that the presence of CCUS projects could drive local economic growth and benefit nearby communities through increased employment opportunities (Chen & Jiang, 2022).

This study estimates the net impact of CCUS on the surrounding housing values in the U.S. Using high-resolution spatial data, we provide empirical evidence on how potential environmental and geological impacts are capitalized into the housing market to enable a more precise estimation of the local impacts of CCUS. We leverage the spatial and temporal variations of CCUS projects and daily housing transaction data from 1990 to 2021 to quantify the potential impact. Based on the buffer we calculated, properties located within 15 km of a CCUS project are impacted by the project. We find that the sale price decreases by 10.18% on average as a result of CCUS operations. However, house values increase by 3.6% if they are within 5 km of CCUS facilities. As distance increases, the positive impact decreases and adverse environmental costs become dominant so that the project's impact shifts from being positive to significantly negative.

Our study also differentiates the impact of CCUS projects based on the project type and facility conditions, such as carbon capture projects, carbon storage projects, retrofitted CCUS projects, and new CCUS projects. Sale prices decrease by 9.88% when a carbon capture project is in operation within 15 km and decrease by 6.42% when a storage project is in operation. While retrofitted CCUS projects do not significantly affect nearby housing prices, new-built CCUS projects significantly reduce nearby home prices by 10.68% on average. Our study also uses a triple difference (DDD) approach to distinguish the effects of CCUS projects on housing prices from the effects of oil basins, since CCUS projects are primarily located in oil basins in the U.S. The CCUS operation has a net impact of -17.84% on nearby housing prices when compared to similar houses in oil basins without CCUS operations.

The mechanism analysis reveals that the reduction in housing prices could be attributed to the hindered local economic developments following CCUS projects operating within 15 km, which implies a spatial limit on the positive economic spillovers from CCUS industrial investments (Cheng & Jiang, 2022). Furthermore, the net decline in housing prices caused by CCUS operations may also be attributed to changes in air pollution, since a worsening air environment is likely to result in a decline in property value. Regarding the positive impacts on house values within 5 km of CCUS projects, we find that having a CCUS project within 5 km improves air quality, but the impact on the air quality may not reach a wider impact zone. Also, the low net captured rates may increase air pollution compared to when there is no capture (Jacobson, 2019).

We make two primary contributions to the literature. Firstly, we contribute to the valuation of public and environmental amenities through the application of the hedonic pricing approach. We add to a growing literature on the local impacts of the construction of public transit infrastructure, gas station sites, and renewable energy (RE) projects (Hewitt & Hewitt, 2012; Yang et al., 2020; Zabel & Guignet, 2012). Hewitt and Hewitt (2012) find that houses located close to urban rail stations are more expensive. Gas stations can reduce nearby property values by more than 10% if leaks from underground storage tanks occur at publicized (and more severe) sites (Zabel and Guignet, 2012). Similarly, shale gas development (Muehlenbachs et al., 2015), the conversion of coal-fired power plants into gas-fired power plants (Mei et al., 2021), and urban natural gas leaks (Shen et al., 2021) all have the potential to negatively impact the value of nearby properties. The local impacts of renewable energy projects, such as wind and solar, on housing prices have also been studied in recent research. While it is widely accepted that renewable energy projects have social benefits (such as reducing greenhouse gas emissions), studies also indicate they could lead to a decrease in house values (Dröes & Koster, 2016; Gaur & Lang, 2020; Gibbons, 2015; Jarvis, 2021) because of factors such as blocking of views, noise from wind turbines, and Nimbyism. There are few studies investigating the economic impacts of CCUS specifically. Secondly, our paper adds to the strand of literature that examines public attitudes toward CCUS projects by revealing preferences in the United States. Through surveys, Liu et al. (2021) and Linzenich et al. (2019/2021) examined public perceptions of CCUS projects in China and Germany, respectively. There is conflicting evidence regarding how individuals value CCUS projects (Sun et al., 2020). The study provides useful insights into how CCUS projects may be expanded efficiently as possible opposition from residents may lead to increased tensions, similar to what was observed when wind and solar projects were expanded (Carlisle et al., 2015). Our findings have important implications for the successful expansion of CCUS projects on a large scale around the globe.

2 Materials and Methods

2.1 Data

The Global CCS Institute[1] contains the project level information for all CCUS projects in the U.S., including the first year in operation, technology details, ownership, facility category (commercial or demonstration), facility industry (natural gas processing, power generation, hydrogen production, fertilizer production, refining, ethanol production, etc.), and facility location. In total, there are 21 projects in operation, 14 projects completed, and 2 projects' operations in suspension as of January 2022.

Our study includes 26 CCUS projects that are not located in remote areas (i.e., have residential communities within 10 miles). **Figure 1** illustrates the locations of 26 CCUS sites in our sample. CCUS projects in the United States are typically located in oil and gas fields or basins. The operational years of the 26 CCUS projects range from 2000 to 2018. We consider two important features when analyzing the impact of CCUS projects on nearby property values, including project type and whether the project is retrofitted. 17 of the CCUS projects are carbon capture projects, while 12 are carbon storage projects, and 3 are both carbon capture and storage projects. Carbon capture projects include carbon capture facilities, carbon capture tests, and carbon capture technology tests. Carbon storage projects include carbon storage

[1] Global CCS Institute. https://co2re.co/FacilityData.

facilities, enhanced oil recovery (EOR) projects, storage performance tests, and CO2 injection and monitor projects. Three projects are both carbon capture and storage projects (site17, site 26, and site31). As for facility conditions, 20 of them are new-built projects, while 6 are retrofitted projects. Retrofitted projects in our sample include (1) projects retrofitting a CO_2 capture/storage facility (site1, site16, site26 in the Supplementary Tables A1 and A2) or a closed well (site24), or (2) a CO_2 capture facility is retrofitted to an existing power plant or a production unit of a plant (site30, site31).[2]

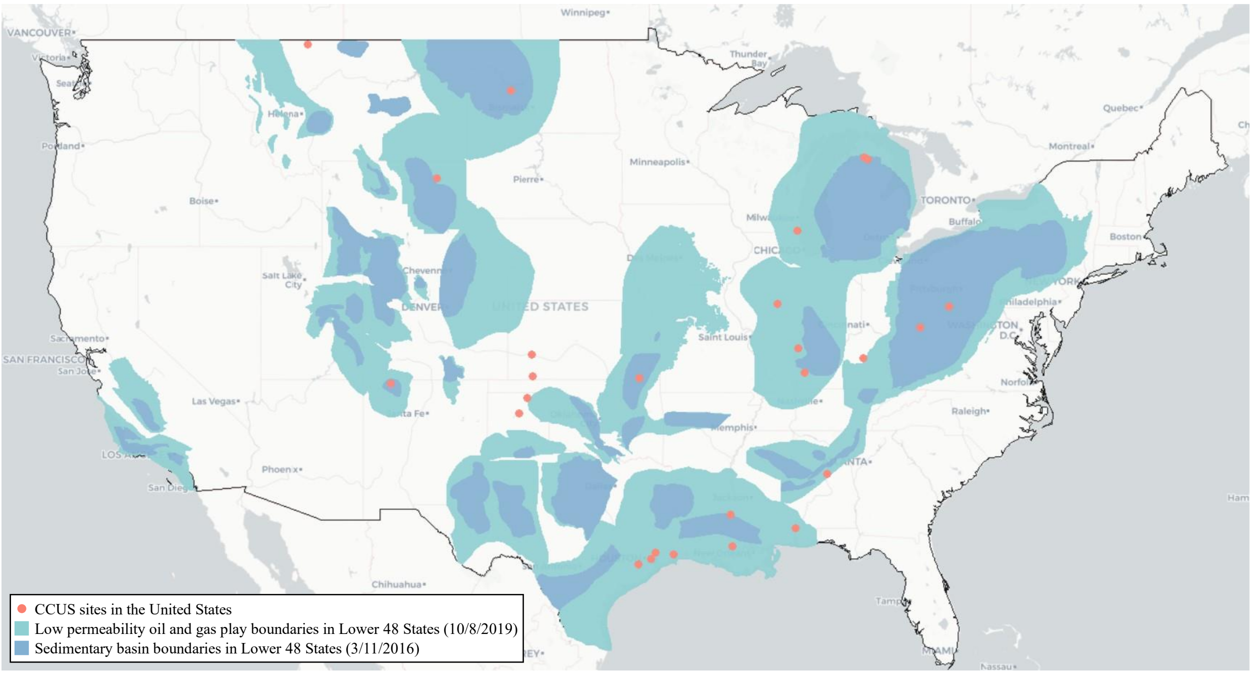


Figure 1. An overview map of CCUS site locations in the sample, along with boundaries of basins and oil/gas fields in the United States.

Individual housing transaction data is provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX)[3]. The dataset provides historical transaction and assessment records (including sale prices, locations, translation dates, etc.) with property-level building attributes such as the number of rooms, building area, land values, and year built. We match these houses with nearby CCUS projects based on the longitudes and latitudes. There are 4,699,009 transactions of properties located within 100 km of a CCUS project from 1990 to 2021.[4]

We also collect an extensive set of explanatory variables to mitigate potential omitted variable concerns. Data on boundaries of basins and oil and gas fields are from U.S. Energy Information Administration (EIA)[5]. Data on population density and personal income per capita (1969-2020) are retrieved from the

[2] See Supplementary Tables A1 and A2 for detail information of each site. The site id here is labelled by the authors for ease of exposition. Information of retrofitted CCUS projects in the U.S. are from ZEROCO2.NO (http://www.zeroco2.no/projects/countries/usa).
[3] Zillow. (2021). Zillow's Assessor and Real Estate Database. https://www.zillow.com/research/ztrax/.
[4] Since the operational years of CCUS projects in our sample range from 2000 to 2018, we exclude housing transactions that occurred before 1990. We believe transactions occurring more than ten years prior to CCUS projects' operation do not contribute more to our analysis. Our final sample consists of transactions from 1990 to 2021.
[5] EIA. Maps: Oil and Gas Exploration, Resources, and Production. U.S. and lower 48 states. Map data. https://www.eia.gov/maps/maps.htm.

Bureau of Economic Analysis, US Department of Commerce[6]. Data on annual electricity prices (1990-2020)[7] and monthly natural gas prices (1989-2021)[8] are obtained at the state level from EIA. Data on environmental awareness, measured by the percentage of residents that believe global warming is happening (2020), is obtained from the Yale Program on Climate Change Communication[9]. Texas traffic flow data (2002-2021) is collected at the monitoring site level from the Texas Department of Transportation[10]. Texas Data on PM10 (1990-2021) at the monitoring site level is obtained from the United States Environmental Protection Agency (EPA)[11]. The number of business establishments at the zip-code level (1994-2020) is obtained from the U.S. Census Bureau[12].

Housing prices are converted into 2021 dollars adjusted for inflation. In **Table 1**, 21 states have houses located within 100 km of a CCUS site. Our sample contains more than 2.7 million houses in Illinois, but only 80 are from New Mexico. Mississippi has the lowest average property price, $58,497, while Colorado has the highest at $356,584 in our sample. **Table 2** compares the building characteristics between treatment and control houses in this study. The first three columns contain summary statistics for the treatment and control houses from the full sample, a repeated sales sample, and a cross-sectional sample after matching. Our main model is based on repeated sales. Columns 4 and 5 present t-test results that compare building characteristics of three samples. Column 4 compares full and repeated samples, whereas column 5 compares repeated and cross-sectional samples. Houses in the treatment group are within the impact buffer of CCUS projects, whereas houses in the control group are outside the buffer (but still within 100 km[13] of the nearest CCUS project). The term buffer refers to the distance beyond which CCUS projects do not affect the housing market in the surrounding area. Detailed information regarding buffer estimation is provided in the section on empirical strategy. When comparing the treated group with the control group, we find that the treated buildings are newer, smaller (in terms of building area), more expensive (in terms of land value), and have a smaller number of rooms and stories than the control houses on average.

Table 1. The distribution of houses and descriptive statistics of housing prices.

State	No. of houses	Average House Price ($ in 2021)	Std. Dev. of House Price
AL	420,376	198,145	223,524
CO	23,084	356,584	329,905

[6] Bureau of Economic Analysis, US Department of Commerce. Regional data: GDP and income. https://apps.bea.gov/iTable/index_regional.cfm.
[7] EIA. Detailed State Data. https://www.eia.gov/electricity/data/state/.
[8] EIA. Natural gas prices. https://www.eia.gov/dnav/ng/ng_pri_sum_a_EPG0_PRS_DMcf_m.htm.
[9] Yale Program on Climate Change Communication. https://climatecommunication.yale.edu/visualizations-data/#visualizations-data-search-filter.
[10] Texas Department of Transportation. TxDOT AADT Annuals. https://gis-txdot.opendata.arcgis.com/datasets/TXDOT::txdot-aadt-annuals/explore?location=30.920999%2C-100.075333%2C6.51&showTable=true.
[11] United States Environmental Protection Agency. Annual Summary Data. Concentration by Monitor. https://aqs.epa.gov/aqsweb/airdata/download_files.html#Meta.
[12] County Business Patterns (CBP) Datasets, US census bureau. https://www.census.gov/programs-surveys/cbp/data/datasets.html.
[13] Despite not expecting the impact of CCUS to reach a radius of 100 km, we choose 100 km to include enough properties for the control group. Choosing 100 km is a conservative choice. An additional robustness check is conducted later by changing the outer boundary of the control group from 30 km to 100 km. The robustness check illustrates that our main results are not sensitive to the outer boundary we chose.

FL	117,048	175,954	196,515
IL	2,737,221	328,969	326,238
IN	3,410	63,917	118,072
KS	114	79,054	68,623
KY	290,692	210,290	230,498
LA	180,069	210,353	227,851
MI	26,911	121,606	135,754
MO	337	63,307	53,754
MS	237	58,497	82,858
ND	8,118	216,338	142,602
NM	80	139,393	83,983
OH	73,369	116,220	160,650
OK	46,082	168,760	180,389
PA	133,960	173,206	190,389
TN	85,455	182,634	188,200
TX	43,546	102,593	143,354
WI	456,812	246,580	311,859
WV	51,883	164,150	168,350
WY	205	166,108	81,304

Table 2. Comparison of full sample, repeated sales sample, and cross-sectional matched sample concerning building characteristics between treatment and control houses.

	Full sample	**Repeated sales sample**	**Cross-sectional sample**	***p*-value (1) versus (2)**	***p*-value (2) versus (3)**
	(1)	(2)	(3)	(4)	(5)
No. of Treated Houses	**156,680**	**85,434**	**22,555**		
Year built	1971.86	1971.94	1976.92	0.5984	0.0000
No of stories	1.36	1.38	1.41	0.0000	0.0000
Total rooms	3.08	2.44	3.15	0.0000	0.0000
Total bedrooms	2.85	2.92	3.16	0.0000	0.0000
Building area (Sq Ft)	3859.89	3541.10	4229.05	0.0000	0.0000
Land value ($)	27826.17	24609.66	19236.33	0.0000	0.0000
No. of Control Houses	**7,112,790**	**4,613,575**	**21,877**		
Year built	1967.65	1966.82	1975.62	0.0000	0.0000
No of stories	1.86	1.99	1.53	0.0000	0.0000
Total rooms	4.92	5.10	3.2	0.0000	0.0000
Total bedrooms	3.01	3.09	3.18	0.0000	0.0000
Building area (Sq Ft)	4146.44	3757.89	4332.99	0.0000	0.0000
Land value ($)	22595.74	20127.72	20279.66	0.0000	0.6615

Notes: Control houses are located between 15 km and 100 km from CCUS projects, whereas treated houses are within 15 km based on buffer estimation later.

2.2 Empirical strategy

As shown in **Figure 1**, basins are frequently chosen as the sites of CCUS project constructions, as are oil and gas fields, saline aquifer traps, and saline aquifers outside of traps and onshore sites (Gough and Shackley, 2006). Therefore, self-selection based on location is one of the concerns of this study. Furthermore, there may be concurrent changes occurring alongside the construction of the CCUS, such as the construction of shopping malls and the development of other local infrastructures. To control for potential endogeneity and contemporaneous changes, first, we use a repeated sales data sample with individual fixed effects, in addition to a series of time fixed effects (month-of-sample, and county-by-year fixed effects) to capture the time-invariant factors at the level of individual houses and the time-varying factors at the county level. To avoid the impact of remodeling on housing prices, houses that were remodeled after 2000 are excluded from the analysis. Second, we estimate a buffer based on building features and the distance from the building to the CCUS to identify which buildings are located within close proximity to the CCUS (e.g., Muehlenbachs et al., 2015), which avoids arbitrarily defining the treatment distance as inappropriate buffer selection could introduce bias into the study. Third, we employ an event study analysis in a difference-in-differences framework to demonstrate that price trends are comparable before the treatment and argue that the estimated positive effects are unlikely to be caused by unobserved, differential trends between control and treatment groups. Fourth, we utilize a matching approach to construct a more balanced control group based on a rich set of observables. Houses assigned to the control group are sold during the same transaction year and belong to the same county as those assigned to the treatment group. Fifth, since being located within a basin might affect property values, we employ a DDD approach to distinguish between CCUS and basin effects on housing prices. We compare property values near CCUS projects to those farther away, properties in basins with CCUS to those without CCUS, and properties sold before and after CCUS operation. Lastly, we consider other contemporaneous changes, such as traffic flow and air pollution, to investigate the mechanisms by which CCUS impacts are capitalized into nearby property values. The following sections provide a detailed description of our empirical strategies.

2.2.1 Buffer

To define the "buffer" of adjacent properties, we follow the method employed by Muehlenbachs et al. (2015), which compared the prices of properties sold before and after CCUS projects were operational to determine the distance beyond which CCUS facilities no longer have an impact on property values.

First, we select a subset of properties that have been sold more than once and have at least one transaction made after the operation of one CCUS facility within 100 km.[14] Second, we estimate the residuals of a regression that controls for county-by-year fixed effects, month-of-sample fixed effects, business establishments by zip-code level, and property-level building characteristics (including building age, number of stories, number of bedrooms, number of rooms, building area (in square footage), garage area (in square footage), and land assessed value. The CCUS fixed effects and the property fixed effects are collinear, so we drop the CCUS fixed effects. Third, we estimate two price functions based on the distance to the nearest CCUS site: one for properties sold before the CCUS operation, and one for

[14] We choose to only look at houses that have *one* CCUS facility within 100 km, as it would be difficult to separate the impact of the nearest CCUS facility before and after the facility is operational if the house was already being impacted by another CCUS project nearby. We choose 100 km to include enough properties for constructing the control group even though we do not expect the impact of CCUS to reach a 100-km radius. The 100-km is a conservative choice. We also carry out an additional robustness check later, where we change the outer boundary of the control group from 30 km to 100 km. We find that our main results are not sensitive to the outer boundary we selected.

properties sold after. We estimate price functions by using local polynomial regressions with the residuals in the last step as the dependent variables.

2.2.2 DID estimation

We estimate the overall net effect of the CCUS operation by using the difference-in-differences (DID) methodology. Only properties that have been sold at least twice during the sample period are included in our main estimation. We also exclude houses from our sample that were remodeled after the year 2000 (about 1.4% of the total sample) to eliminate any influence of remodeling on the estimation of a price premium. By using a DID model based on repeated sales, we compare the prices of the same houses rather than comparing houses with different characteristics. The repeated sale sample and full sample share many of the same characteristics, including building age, number of stories, number of rooms, number of bedrooms, and garage area (see column 4 in **Table 2**). The percentage differences[15] between the two sample groups on housing price, building age, number of stories, number of rooms, number of bedrooms, building area, land value, and garage area are 4.01%, 0.95%, 5.74%, 4.65%, 2.63%, 7.18%, 10.78%, and 5.82%, respectively. We also conduct a two-sample t-test which shows the differences between the full sample and repeated sample are statistically significant, potentially due to a large sample size. As a result, it is important to use the DID approach to eliminate such differences in the levels of building attributes. The DID model is specified as follows:

$$lnY_{ict} = \alpha D_{it} + \beta BA_{it} + \rho BE_{zy} + \gamma_i + \sigma_c \times \vartheta_y + \mu_m + \varepsilon_{ict} \tag{1}$$

where lnY_{ict} is the natural logarithm of the sales price of house i at day t in county c. Housing prices are converted into 2021 dollars adjusted for inflation rates. D_{it} takes a value of one only if house i is in the treatment group (located within the buffer zone) and the post-treatment period. The post-treatment period is determined by the operational year of the nearest CCUS project. For operations-in-suspension projects, the post-treatment period includes the period following suspension. Despite the suspension of the CCUS facility, we assume that its existence continues to influence nearby housing prices. γ_i controls individual fixed effects. $\sigma_c \times \vartheta_y$ represents county-by-year fixed effects, and μ_m represents month-of-sample fixed effects. In our sample, one house is assigned to only one CCUS project, the one that is closest to it. This leads to a collinearity between property fixed effects and CCUS fixed effects. The CCUS fixed effects are therefore eliminated. BA_{it} is the building age of house i at day t. BE_{zy} is the business establishments of zip code z at year y. ε_{ict} is an idiosyncratic error term. We cluster our standard errors at the individual house in our main model, allowing for correlations between observations within the same house. The standard errors are also clustered by county in another model specifications, and the results are presented in Table A3. We use 14 distance bins, ranging from 2 km to 15 km, with a 1 km increment, to determine how the effects differ as we change the size of the adjacency buffer. There is a limited number of houses within 1 km of CCUS projects (86, which accounts for only 0.002% of our sample). We also use the same method to determine whether retrofitting the facilities and specific functions of the project have different effects on housing prices.

2.2.3 Cross-sectional analysis with propensity score matching (PSM)

A DID approach relies upon intertemporal price variation. A shift in the hedonic gradient over time, however, can bias the estimations (Kuminoff and Pope, 2014). Muehlenbachs et al. (2015) propose an alternative approach for addressing this problem based on cross-sectional data and nearest-neighbor matching where the treatment and control groups have identical characteristics except for the treatment variable to minimize selection bias. Based on the conditional independence assumption (Angrist and

[15] The percentage difference is calculated by dividing the absolute difference between two numbers by their average and then multiplying by 100%.

Pischke, 2008), nearest-neighbor matching controls the selection bias of the method based on the observed features or covariates. Despite this, the matching covariates in our dataset may not contain all the important house features. Thus, the cross-sectional estimation with matching is served as a robustness check while the DID specification is still preferred as the DID better controls time-invariant, unobserved variables.

We first perform an exact match in the time dimension (transaction year) to account for unobservable time-variant factors, and in the geographic dimension (county) to account for unobservable neighborhood factors. A propensity score match (PSM) is then applied to identify one nearest neighbor in the control group for each treated house according to time-invariant features of the building (Qiu, Wang, and Wang, 2017). Key house characteristics such as building age, the number of bedrooms, building area, and land value are used as covariates for matching. We then use the matched sample to conduct an ordinary least squares (OLS) model by regressing the log of house sales prices on a treatment dummy variable, house characteristics, and business establishments to control for local economic activities. Post-treatment dummies are coded as one for houses treated after CCUS operation, otherwise as zero[16]. A set of fixed effects are also included, such as county-by-year, month-of-sample, and CCUS fixed effects.

2.2.4 Triple difference (DDD) estimation

In **Figure 1**, most CCUS projects are located within oil basins, thus making it difficult to distinguish between CCUS impact and basin impact on nearby housing prices. For CCUS projects added to existing oil basins, the DDD approach is applied in order to further control for differences in trends as well as any contemporaneous changes between the control and treatment groups. DDD enables us to compare the values of properties near CCUS projects (i.e., within treatment buffer zones) to those further away, properties in oil basins with CCUS to those in oil basins without CCUS, and properties sold before CCUS operations to those sold after CCUS operations. The DDD approach primarily uses data from Illinois, Kentucky, and Wisconsin since these states have enough data to perform this analysis. The DDD is specified as

$$lnY_{ict} = \beta_1 CCUS\ treat_{it} + \beta_2 Basin\ treat_{it} + \beta_3 Post_{iy} + \beta_4 CCUS\ treat_{it} * Basin\ treat_{it} + \beta_5 CCUS\ treat_{it} * Post_{iy} + \beta_6 Basin\ treat_{it} * Post_{iy} + \beta_7 CCUS\ treat_{it} * Basin\ treat_{it} * Post_{iy} + \alpha BA_{it} + \rho BE_{zy} + \gamma_i + \sigma_c \times \vartheta_y + \mu_m + \varepsilon_{ict} \qquad (2)$$

where lnY_{ict} is the natural logarithm of the sales price of house *i* at day *t* in county *c*. Housing prices are converted into 2021 dollars adjusted for inflation rates. $CCUS\ treat_{it}$ takes a value of one only if house *i* is in the treatment group (located within the buffer zone) of CCUS projects, and zero if house *i* is outside the buffer zone but still within 100 km of the nearest CCUS project. $Basin\ treat_{it}$ equals one if house *i* is located inside an oil basin, and zero if house *i* is located outside an oil basin but within 50 km of its edge. $Post_{iy}$ takes the values of one if the transaction year *y* of house *i* is after the operational year of the closest CCUS project, and zero otherwise. The DDD coefficient β_7 estimates the difference between two DIDs, i.e., how the presence of CCUS projects changed the treatment effect on nearby housing prices. γ_i controls individual fixed effects. $\sigma_c \times \vartheta_y$ represents county-by-year fixed effects, and μ_m represents month-of-sample fixed effects. As CCUS fixed effects and property fixed effects are collinear, CCUS fixed effects are dropped. BA_{it} is the building age of house *I* at day *t*. BE_{zy} is the business establishments

[16] As part of our sample, we consider CCUS projects that are completed, currently in operation, or currently in suspension in the United States. Post-treatment periods are based on the operational year of each CCUS project, regardless of whether the project has been suspended, as we anticipate that the presence of suspended CCUS facilities will still have an impact on nearby property values.

of zip code *z* at year *y*. ε_{ict} is an idiosyncratic error term. We cluster our standard errors at the individual house.

2.2.5 Heterogeneity analyses

To examine the heterogeneity of the price premium, a flexible semiparametric approach using the partially linear varying coefficient fixed effects panel data is employed. The model is specified as follows:

$$lnY_{iy} = D_{iy} \times g(U_{iy}) + \boldsymbol{X'}_{\boldsymbol{iy}}\boldsymbol{\theta} + \rho_j + \vartheta_y + \varepsilon_{iy} \quad (3)$$

where lnY_{iy} is the natural logarithm of the sales price at the zip-code zone *i* in year *y*. Housing prices are converted into 2021 dollars adjusted for inflation rates. We collapse the data at the zip code zone × year level so that we have observations each year to support such analysis. D_{iy} is the treatment variable with a functional coefficient $g(U_{iy})$ and U_{iy} is a continuous variable to be examined for heterogeneity, including environmental awareness at the county level, business establishments at the zip code level, and industry of the CCUS projects. $\boldsymbol{X'}_{\boldsymbol{iy}}$ is a vector of covariates such as federal fund rates, demographic features by county level, and the price of electricity and natural gas by state level. ρ_j controls CCUS fixed effects. ϑ_y represents year-fixed effects. ε_{iy} is an idiosyncratic error term.

2.2.6 Mechanism analysis

We also examine the mechanisms underlying price reductions after CCUS operation using Texas data, since Texas has five CCUS sites, making it the state with the largest number of CCUS projects in our dataset. Specifically, we examine whether there are changes in air pollution and traffic flows following the CCUS operation. The following model is applied:

$$lnT_{iy} = \beta D_{iy} + \boldsymbol{X'}_{\boldsymbol{iy}}\boldsymbol{\theta} + \gamma_i + \sigma_c \times \vartheta_y + \varepsilon_{iy} \quad (4)$$

where T_{iy} is the traffic volume (average annual daily traffic, AADT) or air pollution (PM10 concentration) at the monitoring station level for the house *i* in year *y*. D_{iy} equals 1 only if house *i* is in the treatment group (located within the buffer zone) and the post-treatment period, and 0 otherwise. $\boldsymbol{X'}_{\boldsymbol{iy}}$ controls for covariates such as business establishments, personal income per capita, and population density. γ_i controls individual fixed effects. $\sigma_c \times \vartheta_y$ represents county-by-year fixed effects. We eliminate CCUS fixed effects due to their collinearity with property fixed effects.

2.2.7 Event study analysis

An event study analysis for DID is conducted to verify the plausibility of the parallel trend assumption between houses with and without nearby CCUS projects. When two groups of houses exhibit a parallel trend, there does not appear to be a systematic difference as the difference between the two groups remains constant over time, thus supporting the validity of our DID analysis. Our strategy is similar to Dobkin et al. (2018) in which we limit the sample of observations to five waves prior to the CCUS operation and five waves after it and exclude the period right before the CCUS operation (where m = 1). But it should be noted that the coefficient for a given lead or lag may be contaminated by other period effects. To adjust bias, we employ an alternative estimator free of contamination following Sun and Abraham (2021).[17] Below is the specification of the event study model:

$$lnY_{iy} = \alpha BE_{iy} + \boldsymbol{X'}_{\boldsymbol{iy}}\boldsymbol{\beta} + \sum_{m=2}^{M} \rho_m (Lag\ m)_{it} + \sum_{n=1}^{N} \delta_n (Lead\ n)_{it} + \gamma_i + \sigma_c \times \vartheta_y + \varepsilon_{iy} \quad (5)$$

[17] It is a Stata command called *eventstudyinteract*, and its source code can be found at https://github.com/lsun20/EventStudyInteract.

where lnY_{iy} is the natural logarithm of the sales price of zip-code zone *i* at year *y*. Housing prices are converted into 2021 dollars adjusted for inflation rates. *M* and *N* represent lags and leads, indicating the number of years away from the operation of CCUS projects. The baseline omitted case is the first lag where m = 1. Data is collapsed at the zip-code zone × yearly level to ensure we have observations during each year for analysis (which is not possible with individual houses). Considering the wide buffer in our analysis, we use the average distance between houses in a zip-code zone and the nearest CCUS project in determining whether to assign the zip-code zone to treatment. The zip code zones near CCUS projects (average distance less than 15 km) are coded as treated and others are coded as control. γ_i controls zip-code fixed effects. $\sigma_c \times \vartheta_y$ represents county-by-year fixed effects. We assign only the nearest CCUS project to each zip code in the area based on the average distance between houses within the zip code and the CCUS project. Thus, the zip-code fixed effects and the CCUS fixed effects are collinear, and the CCUS fixed effects are therefore removed from the analysis. BE_{iy} is the business establishments of zip code *i* at year *y*. $\boldsymbol{X'}_{\boldsymbol{iy}}$ consists of a series of covariates, including building characteristics, demographic features, and control variables such as federal fund rates, electricity prices, gas prices, PM 2.5 concentration, and environmental awareness about whether global warming is happening. ε_{iy} is an idiosyncratic error term. We cluster our standard errors at the zip-code level.

In addition, we also conduct an event study analysis for DDD. The sample of observations is limited to the eight waves prior to and eight waves following the CCUS operation, excluding the period right before the operation (m = 1). Following is the specification of the event study model for the DDD approach:

$$lnY_{ict} = \alpha BE_{zy} + \boldsymbol{X'}_{\boldsymbol{it}}\boldsymbol{\beta} + \sum_{m=2}^{M} \rho_m (Lag\ m)_{it} + \sum_{n=1}^{N} \delta_n (Lead\ n)_{it} + \gamma_i + \sigma_c \times \vartheta_y + \mu_m + \varepsilon_{ict} \quad (6)$$

where lnY_{ict} is the natural logarithm of the sales price of house *i* at day *t* in county *c*. Housing prices are converted into 2021 dollars adjusted for inflation rates. *M* and *N* represent lags and leads, indicating the number of years away from the operation of CCUS projects. The baseline omitted case is the first lag where m = 1. Houses located in the buffer zone (within 15 km) from a CCUS project are coded as treated and others are coded as control. γ_i controls individual fixed effects. $\sigma_c \times \vartheta_y$ represents county-by-year fixed effects, μ_m represents month-of-sample fixed effects. We exclude CCUS fixed effects from our analysis due to their collinearity with property fixed effects. BE_{zy} is the business establishments of zip code *z* at year *y*. $\boldsymbol{X'}_{\boldsymbol{iy}}$ includes a series of covariates, such as building age, real income per capita, and population density. ε_{ict} is an idiosyncratic error term. We cluster our standard errors at the individual house level.

2.2.8 DID robustness check: changing the outer boundary of the control group

For robustness checks, we change the outer boundary of the control group by a 10-km distance bin. The outer boundary of the control group, i.e., 100 km, was selected to include enough properties to construct the control group. Our goal is to determine if outcomes are sensitive to the outer boundary we selected in the main model. To accomplish this, we decrease the outer boundary of the control group in a range of 30 km to 90 km. The robustness checks are carried out using the same DID approach as our main model.

3 Results

We first calculate a buffer to determine the ranges of treatment groups near the CCUS projects. Next, we compute the impact of the CCUS operation using ZTRAX data across the United States by applying the DID method. Our robustness test is conducted using cross-sectional data coupled with the nearest neighbor matching. Furthermore, we use a DDD approach to separate the net impacts of CCUS from those of oil basins. We then analyze the heterogeneous treatment effects of CCUS projects in relation to environmental awareness, local economic activity, and industry of CCUS projects. The mechanism by which CCUS operation affects nearby housing prices is also investigated. Our event study evidence indicates that our treatment and control groups had comparable trends before the treatment.

3.1 Defining the Buffer

The results of the local polynomial regression are shown in **Figure 2**. On the vertical axis are the residuals of the log housing price. Residual is defined as the difference between the predicted value and the actual value (Residual = actual Y value − predicted Y value). The predicted value is calculated using a local polynomial regression model based on the building characteristics. **Figure 2** illustrates that both price residuals for properties located more than 15 km from CCUS facilities remain close to zero before and after the facility is operational. The results show that building characteristics can be used to estimate housing prices with reasonable accuracy for houses located outside a 15-km radius of a CCUS project. Within 15 km of a CCUS project, however, both residuals of the sales price before and after CCUS operation are significantly different from zero. It suggests that there is a significant factor contributing to the failure of the prediction, namely the operation of CCUS projects within 15 km. Adjacency impacts are present within 15 km of a CCUS site, thereby supporting our decision to establish a 15 km buffer.

In addition, when we focus on houses within 15 km of a CCUS project, price residuals before and after CCUS operations show different patterns. Before CCUS operations, the price residual is negative, which indicates that the actual property value is lower than it should be based on house features. After CCUS operations, the housing price residual changes depending on distance. The residual is initially positive, meaning that the actual housing price is higher than anticipated. It indicates that property values in the vicinity of CCUS projects seem to be positively impacted. Eventually, the price residual becomes negative, indicating that CCUS projects have a negative impact. Thus, CCUS facilities do not have a monotonic impact on houses within the buffer zone after CCUS operations. As distance increases, the impact shifts from a positive to a negative one. It is possible that properties located near CCUS projects may experience both environmental risks and economic benefits. When the distance is further reduced, the environmental costs may be overshadowed by the economic benefits, suggested by evidence indicating that CCUS developments increase employment (Chen & Jiang, 2022). In this regard, the price of houses adjacent to a CCUS site may increase after it is operational.

It is also noticeable that the residual after CCUS operations is higher than that before operation within a distance of 15 km, however, we cannot reach to the conclusion that nearby property values after operations are higher than those before operations. These two price residuals are calculated based on different predicted models using two sets of data, one is before CCUS operations, the other is after CCUS operations. Thus, they cannot be compared directly.

As part of our main model, we will assess the CCUS impacts on treated versus control houses using 15 km as a buffer. As an additional exploration of the changes in the impact of CCUS projects after operations, we also examine the change of post-treatment effects in a 1 km increment within the 15 km buffer zone.

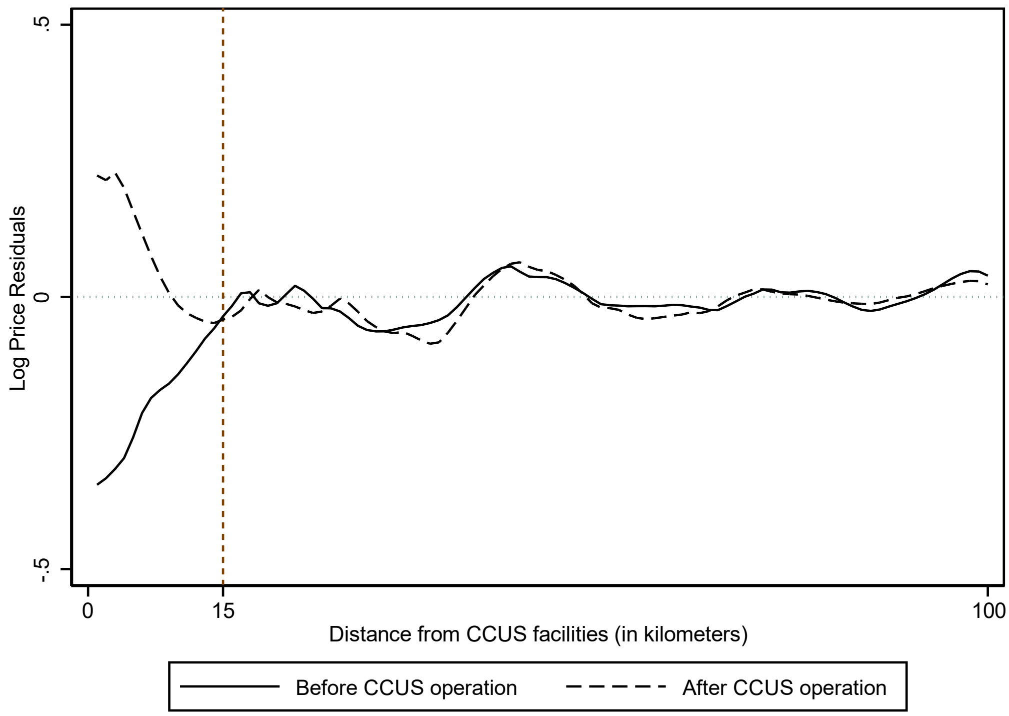


Figure 2. Price Gradient of Distance from CCUS facilities. *Notes*: the buffer is 15 km.

Buffer sizes may vary based on project type and facility condition. A carbon capture project can benefit the environment by reducing greenhouse gas emissions. However, a carbon storage project may lead to leaks in the earth and result in the alteration of geological formations. These projects may have different effects on the housing market in the near vicinity. Moreover, a new construction project is expected to have a greater impact on property values than a retrofitted project, since new construction is built from scratch and is more noticeable, whereas a retrofitted project has already been in place for a considerable amount of time. **Figure 3** illustrates the buffers for carbon capture, carbon storage, retrofits, and new construction. Their impact zones are 15 km, 16 km, 15 km, and 13 km, respectively, which are consistent with the average buffer estimate in **Figure 2**.

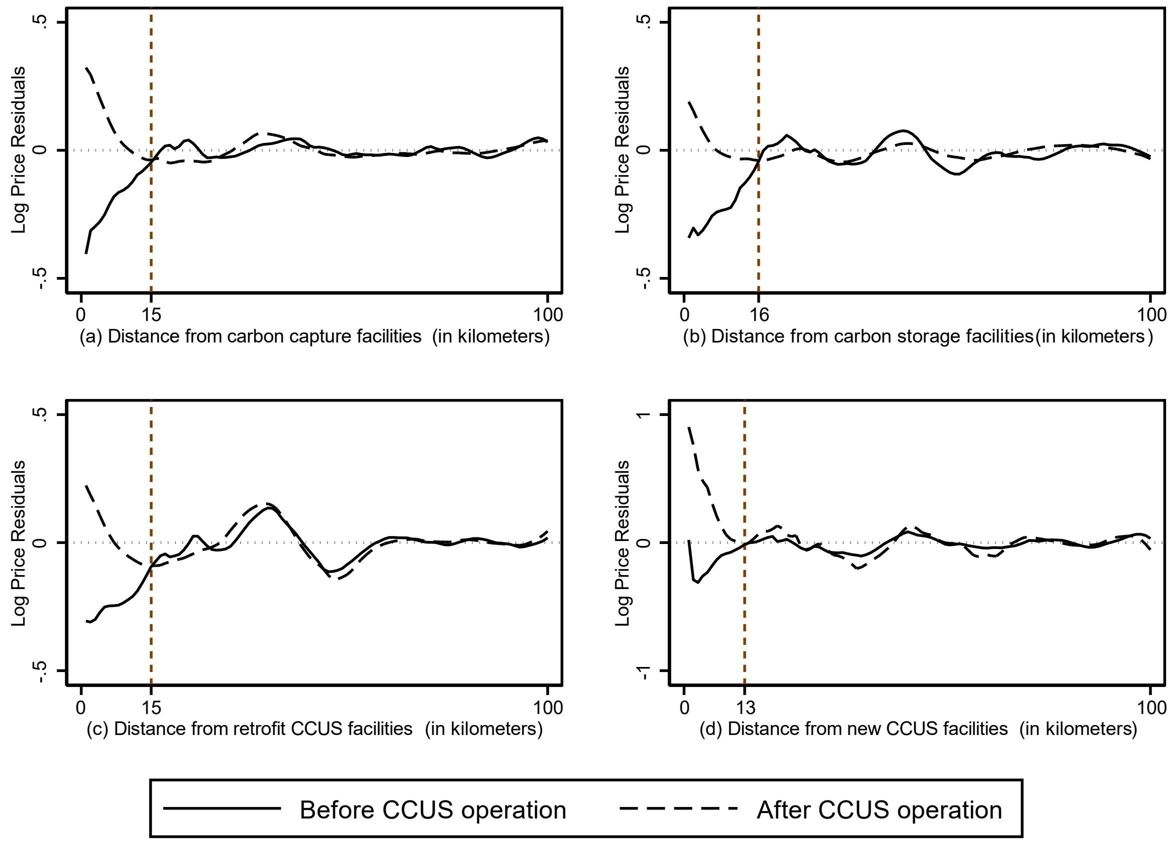


Figure 3. Buffers of different CCUS projects based on project type and facility condition.

3.2 The impact of CCUS projects on home prices

Using the DID model specified in equation (1), we estimate the impact of CCUS projects on the property values of nearby neighborhoods. **Figure 4** illustrates the DID design based on buffer estimation. Only houses located within 100 km of CCUS projects are included in our sample, among which houses within 15 km are assigned to the treatment group, and houses between 15 km and 100 km to the control group. **Figure 5** illustrates our baseline estimation results using a 1 km increment within the buffer, and **Table 3** provides the details of our results. As shown in **Figure 5**, CCUS projects have no significant effect on houses within very close proximity (less than 5 km), possibly due to limited observations (see **Table 3**). As the distance extends to about 5 km, we first observe significant positive adjacency impacts (3.6% increase in property values). A CCUS operation could have beneficial economic consequences, such as the possibility of reusing CO_2 for use in the food industry or other industrial applications. Such increased industrial activity and output will increase the employment rate and economic activity in the local area, resulting in positive effects on property values. The positive effect observed at a 5-km buffer implies that the economic benefits of CCUS projects outweigh the environmental risks for houses located within this buffer zone. There is an insignificant impact at 6 km and 7 km distances as negative impacts begin to emerge and offset the benefits of CCUS operation. From 8 km to 15 km, CCUS facilities have a statistically significant negative impact possibly because projects further away contribute less to economic benefits. The negative impact is over 10%. Housing prices are negatively impacted by proximity to CCUS projects within a 15-km radius. According to the results, operating a CCUS facility within 15 km may cause local homes to lose 10.2% of their values on average.

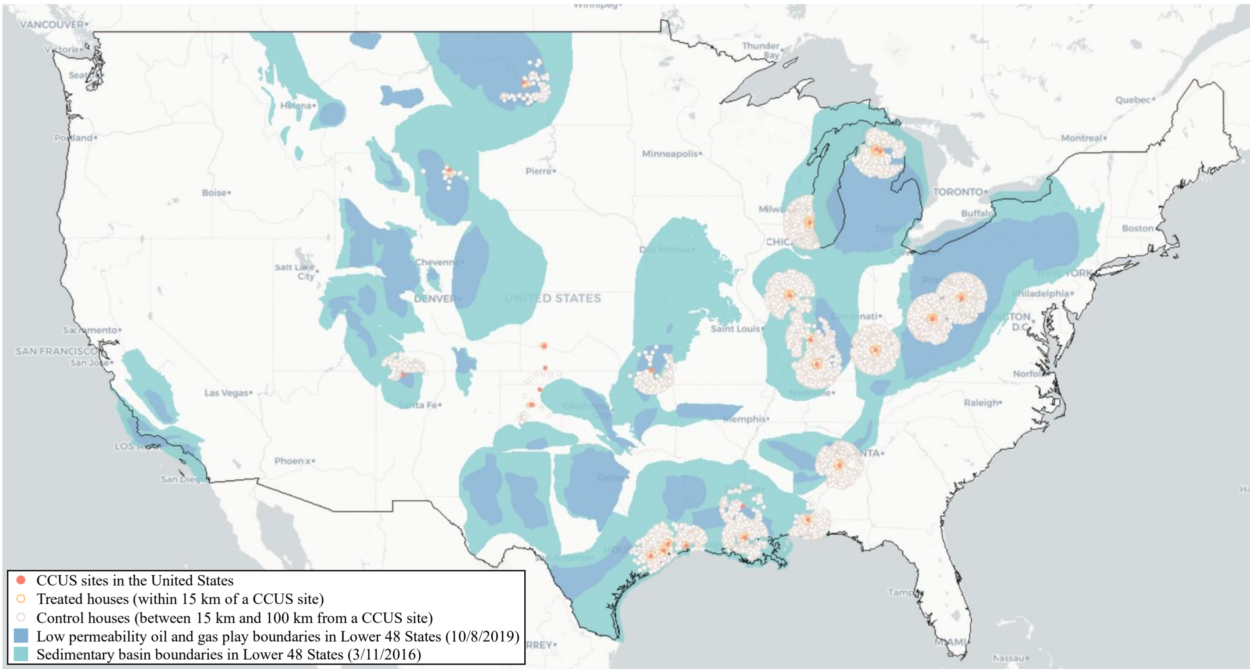


Figure 4. DID design: the treatment and control houses for CCUS projects, along with boundaries of oil/gas fields and basins.

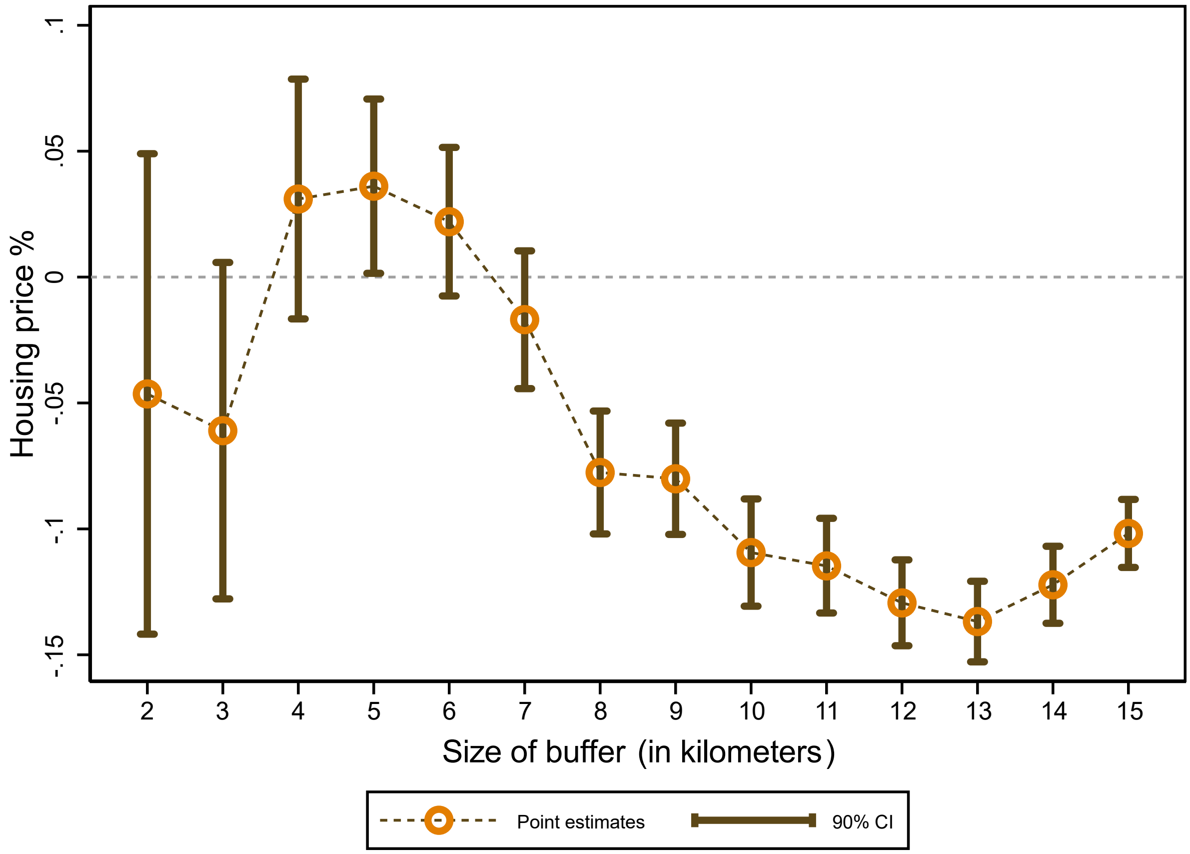


Figure 5. DID results using every 1 km as buffer.

Table 3. The impact of CCUS projects on nearby houses' prices by vicinity.

	Outcome: Natural log of home prices (2021$)													
Buffer	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Coef. of D (ATT)	-0.046	-0.061	0.031	0.036	0.022	-0.017	-0.078	-0.080	-0.109	-0.115	-0.129	-0.137	-0.122	-0.102
p-value	0.424	0.133	0.284	0.086	0.221	0.308	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Robust Std Err	0.058	0.041	0.029	0.021	0.018	0.017	0.015	0.013	0.013	0.011	0.010	0.010	0.009	0.008
90% CI	-0.142	-0.128	-0.017	0.002	-0.008	-0.044	-0.102	-0.102	-0.131	-0.133	-0.146	-0.153	-0.137	-0.115
90% CI	0.049	0.006	0.079	0.071	0.052	0.010	-0.053	-0.058	-0.088	-0.096	-0.112	-0.121	-0.107	-0.088
R-sq	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163
Treated houses	920	2,596	5,455	10,104	15,280	21,884	29,949	39,428	48,341	55,970	63,406	69,542	74,937	85,434
Building age control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business establishments control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-sample FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,585,195													
Groups/Houses	1,438,093													

Notes: Standard errors are clustered at the individual household level. The outcome is the natural log of home prices that are adjusted to 2021$ for inflation. During the post-treatment period, the treated buildings were traded with a nearby CCUS project. Transactions with the treatment (having CCUS projects within 100 km) happened from 1990 to 2021.

The CCUS impacts by project type and facility condition are depicted in Figure 6 and detailed estimation results are presented in Table 4. All models use 15 km as the buffer. As shown in Table 4, column (1) identifies the estimated overall impact of CCUS projects. Overall, CCUS projects reduce nearby house prices by 10.18%, and the result is statistically significant at a 1% level. Column (2) studies only carbon capture projects from the sample where the results demonstrate that carbon capture projects decrease nearby housing prices by 9.88% on average. When only carbon storage projects are examined in Column (3), the results indicate that property values fall by 6.42% with proximity to carbon storage projects. In columns (4) and (5), we examine the impact of retrofit and newly constructed CCUS projects, respectively. Our findings indicate that retrofit CCUS projects do not significantly affect housing prices, while newly built projects reduce home prices by approximately 10.68%. The retrofitted facilities have already existed for a considerable period of time, as opposed to newly constructed facilities for which nearby residents have witnessed the construction process. Consequently, retrofitted CCUS projects are less likely to attract special attention when individuals buying or selling a home in the area. Furthermore, columns (6) and (7) segment new built projects into new carbon capture projects and new carbon storage projects. While both projects have significantly negative effects on property values, new capture projects appear to have a slightly smaller impact than new storage projects. A new capture project reduces nearby housing values by 10.37%, while a new storage project reduces nearby housing values by 13.13%. Similar to our main model, the standard errors are clustered by individual houses. Table A3 presents the results of when we cluster the standard errors at the county level. Overall, all the coefficients remained unchanged as expected, while the *p*-values are higher, making the coefficient of the carbon storage project insignificant when standard errors are clustered at the county level.

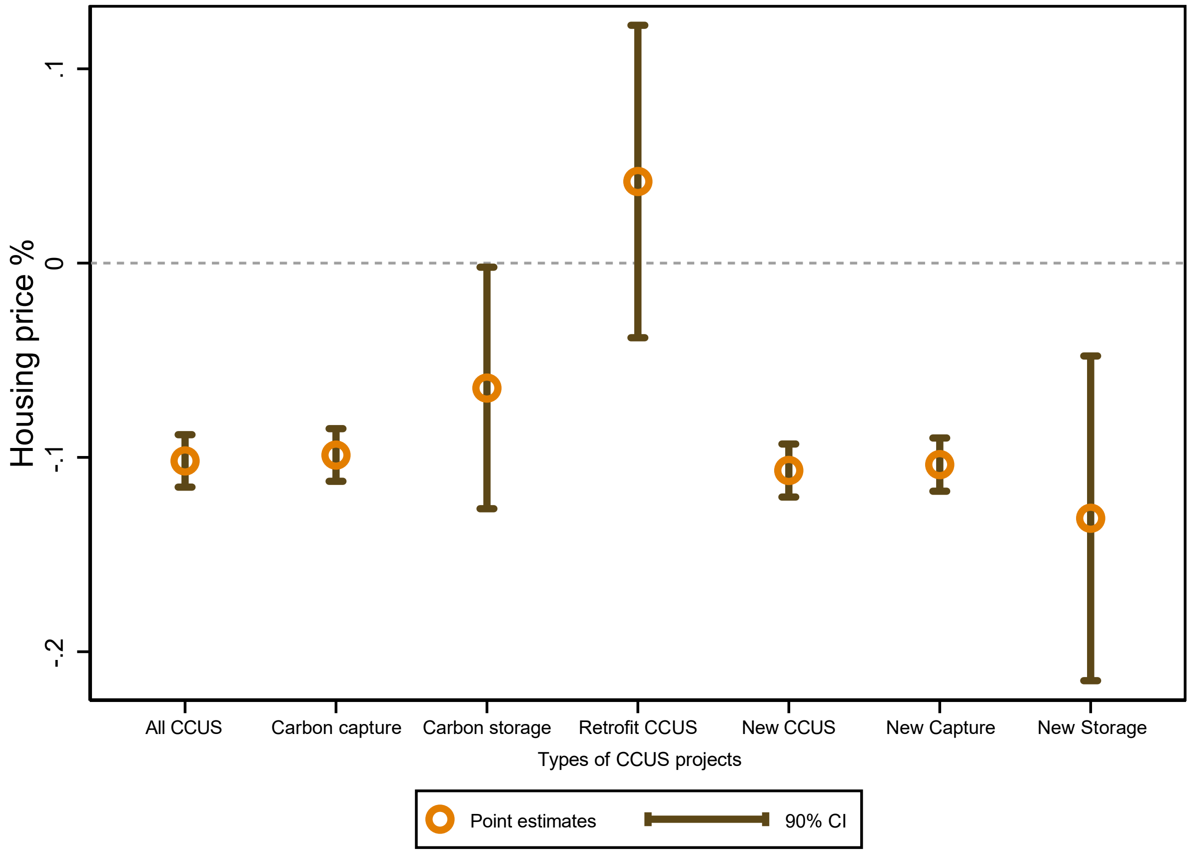


Figure 6. DID results based on project type and facility conditions.

Table 4. The impact of CCUS projects by project type and facility condition on nearby houses' prices.

	Outcome: Natural log of home prices (2021$)						
Model	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Project type	All CCUS	Carbon Capture	Carbon Storage	Retrofit CCUS	New CCUS	New capture	New storage
Coef. of D (ATT)	-0.1018	-0.0988	-0.0643	0.0420	-0.1067	-0.1037	-0.1313
p-value	<0.001	<0.001	0.089	0.390	<0.001	<0.001	0.010
Robust Std Err	0.0082	0.0082	0.0378	0.0489	0.0083	0.0083	0.0508
90% CI	-0.1153	-0.1123	-0.1264	-0.0384	-0.1204	-0.1174	-0.2149
90% CI	-0.0883	-0.0852	-0.0021	0.1224	-0.0931	-0.0900	-0.0478
R-sq	0.163	0.175	0.059	0.058	0.170	0.183	0.063
Observations	3,585,195	3,318,293	459,843	168,244	3,416,951	3,154,147	312,633
Groups/Houses	1,438,093	1,326,630	198,625	76,221	1,361,874	1,252,324	132,179
Treated houses	85,434	77,495	23,935	4,199	81,235	74,039	21,407
Building age control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business establishments control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-sample FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the individual household level. The outcome is the natural log of home prices that are adjusted to 2021$ for inflation. During the post-treatment period, the treated buildings were traded with a

CCUS project nearby. Transactions with the treatment (having CCUS projects within 100 km) happened from 1990 to 2021.

3.3 Cross-sectional results with propensity score matching

Using the propensity score matching approach, we construct an alternative control group. We find a control house that is comparable to the treated house on building covariates, was sold in the same transaction year, and located in the same county as the treated house. **Figure 7** compares the kernel density of the propensity score before and after matching for each state. The propensity scores of treatment households become closer to those of control groups after matching, suggesting that the houses assigned to the control group are more comparable to the treated houses. The OLS regression includes only the matched sample. **Table 5** provides a detailed description of the coefficients. A treatment variable's coefficient represents the estimated ATT. ATT estimates based on cross-sectional data with matching are consistent with DID results. The impact of CCUS on housing prices is still statistically significant, though the magnitude is smaller compared to the DID estimates. All CCUS projects combined reduce nearby housing prices by 8.52% on average. A decline in nearby property value is associated with carbon capture projects, newly constructed projects, and new carbon capture projects, respectively, by 8.32%, 8.40%, and 8.19%. The impact of retrofitting CCUS operations remains insignificant. The impact of carbon storage, however, becomes insignificant when analyzing cross-sectional data with matching. PSM matches the treated and control houses based on building characteristics such as square footage, building age, total bedrooms, and land value. Unfortunately, we do not have access to this information for some houses. Moreover, some treated houses cannot be paired with control houses and do not meet the criteria for matching. Column 5 in **Table 2** compares the summary statistics for the cross-sectional matched sample and the repeated sales sample. A t-test reveals a statistically significant difference between the two samples, perhaps due to the large sample size. Supplementary Figure A1 illustrates the graph of common support.

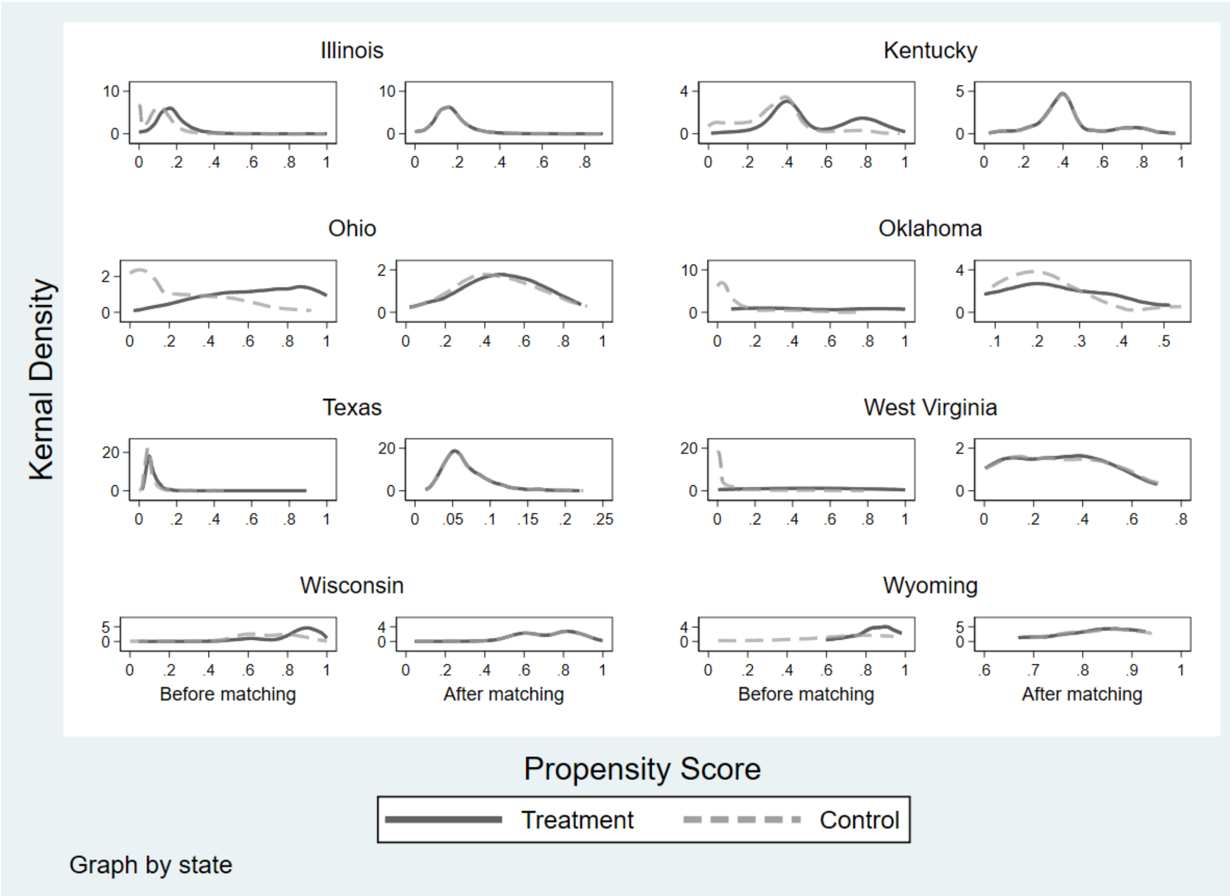


Figure 7. Kernel Density Estimation plots of propensity score before and after matching: treatment group vs. control group. *Notes*: for each pair of the comparison plots, the right one is kernel density of propensity score before matching whereas the left one is after matching. Following is the number of treatment households in each state after PSM: Illinois: 15,944; Kentucky: 1,448; Ohio: 73; Oklahoma: 12; Texas: 1,347; Wisconsin: 3,632; West Virginia: 92; Wyoming: 7.

Table 5. The impact of CCUS projects on nearby houses' prices using matched samples.

	Outcome: Natural log of home prices (2021$)						
Model	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Project feature	All CCUS	Carbon Capture	Carbon Storage	Retrofit CCUS	New CCUS	New Capture	New Storage
Coef. of D (ATT)	-0.0852	-0.0832	-0.0481	-0.0000	-0.0840	-0.0819	0.1277
p-value	<0.001	<0.001	0.815	1.000	<0.001	<0.001	0.892
Robust Std Err	0.0090	0.0089	0.2058	0.1890	0.0089	0.0088	0.9289
90% CI	-0.1000	-0.0979	-0.3888	-0.3115	-0.0986	-0.0964	-1.4642
90% CI	-0.0704	-0.0684	0.2925	0.3115	-0.0694	-0.0675	1.7197
R-sq	0.5150	0.5108	0.6771	0.4779	0.5170	0.5126	0.7999
Observations	42,856	42,727	338	722	42,134	42,005	129
Treated houses	22,555	22,496	165	106	22,449	22,390	59
Business establishments control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
House features control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

CCUS FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-sample FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

3.4 Triple difference (DDD)

We further compare treatment houses and control houses in a basin before and after CCUS operations, as well as treatment houses (located within basins) and control houses outside the same basin without CCUS projects. The differences between the two DIDs are then compared. Since being placed in a basin can also affect housing prices, a DDD approach can be used to estimate the net effect of CCUS on property values. The DDD design is shown in **Figure 8**. A CCUS treatment group within a basin consists of homes located within 15 km of a CCUS project, whereas a CCUS control group within the same basin comprises homes positioned between 15 km and 100 km from a CCUS project. Houses located inside a basin are included in the basin treatment group, while houses outside a basin but within 50 km of the edge of any basin are included in the basin control group. For estimation, we use data from Illinois, Kentucky, and Wisconsin housing transactions and CCUS site data, since these states have a sufficient number of treatment and control projects for both basin and CCUS projects. **Table 6** shows that CCUS operation has a net effect of -17.84% on nearby housing prices compared to houses situated in basins without CCUS projects. Consequently, a house located within close proximity to a CCUS project in a basin is likely to lose 17.84% of its value compared to a house in the same basin without a CCUS project nearby. Moreover, we conducted a robustness check by changing the boundary of the basin control group from 10 km to 100 km by a 10-km distance bin, and DDD results remain the same (see Supplementary Table A4). We find that the DDD results are not sensitive to the 50-km boundary of the basin control group.

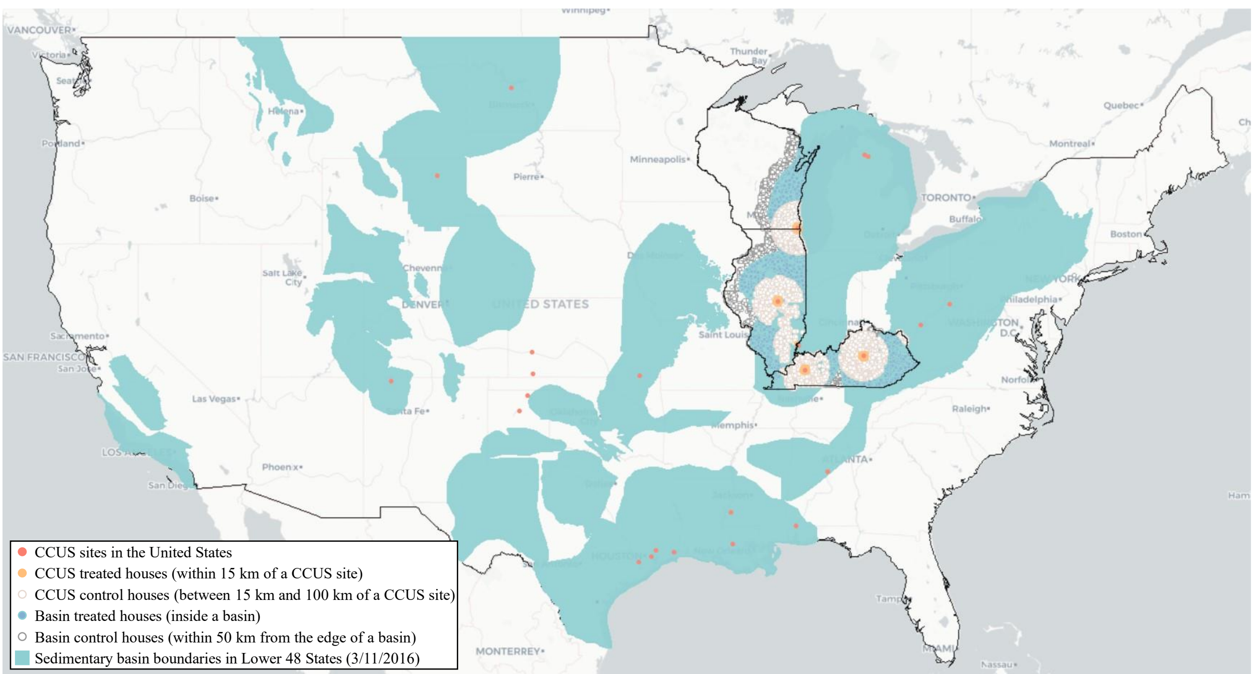


Figure 8. DDD design: the treated and control houses for CCUS projects and basins in Illinois, Kentucky, and Wisconsin.

Table 6. DDD results.

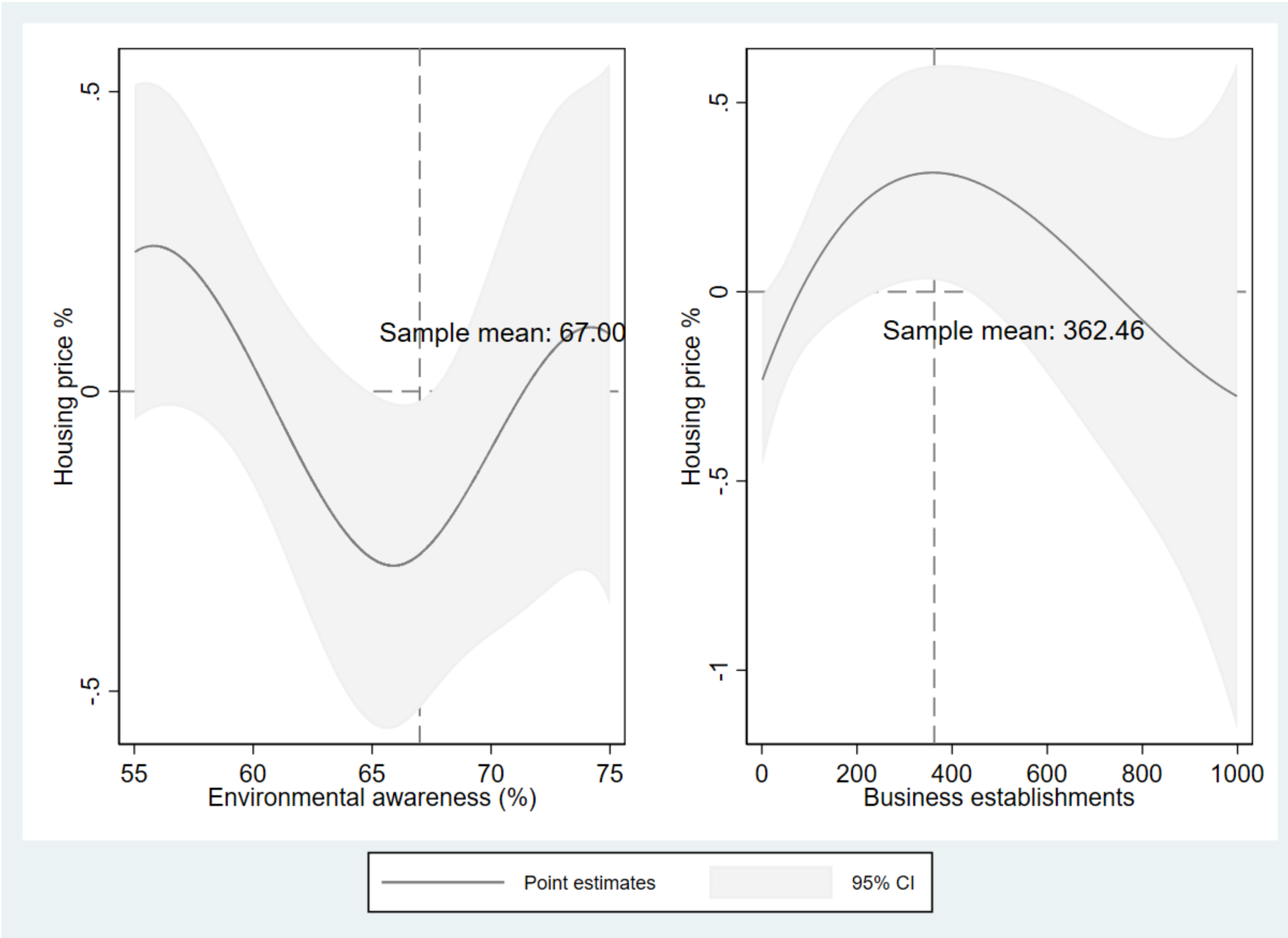
	Outcome: Natural log of home prices (2021$)
Coef. of DDD	-0.1784
p-value	0.000
Robust Std Err	0.0323

90% CI	-0.2315
90% CI	-0.1253
R-sq	0.259
Observations	2,646,882
Building age control	Yes
Business establishments control	Yes
Individual FE	Yes
Month-of-sample FE	Yes
County-by-year FE	Yes

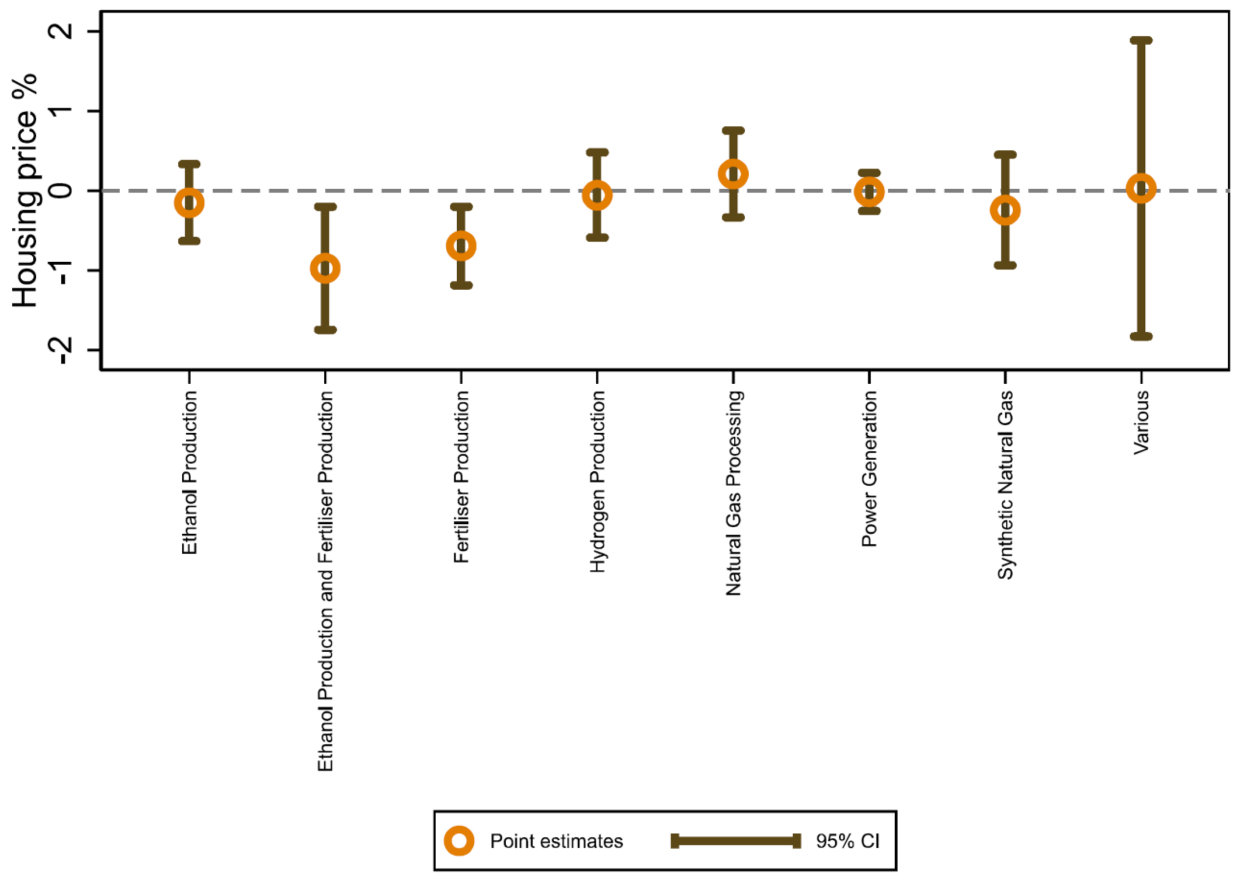
3.5 Heterogeneity

Negative housing premiums resulted from CCUS projects may vary with the socioeconomic characteristics and industries. We explore potential heterogeneity effects by examining the relationship between the impacts of the CCUS facility and other factors, including environmental awareness by county, business establishments by zip code, and the industry by CCUS project. Following Shen et al. (2021), we use a flexible semiparametric approach for fixed effect panel data, which allows for linearity in some variables and non-linearity in others when estimating non-linear heterogeneity.

As shown in **Figure 9**, those with lower environmental awareness are less likely to pay attention to CCUS operations when purchasing or selling a home. People of higher awareness are also not concerned with the operation of CCUS. It is possible that these individuals are also wealthy, and as a result, they purchase homes in expensive and convenient locations. CCUS projects are often located in locations such as oil and gas fields, which are not wealthy individuals' first choices for housing. The average level, on the other hand, reacts strongly to CCUS locations, suggesting they are only interested in purchasing a house near the CCUS projects if the housing prices are substantially reduced. The number of business establishments, such as shopping malls, measures the activities of the local economy. In areas with fewer business establishments, people are reluctant to live close to CCUS facilities unless the housing price is lowered. Therefore, CCUS projects are negative signals for potential buyers in the housing market. It is likely that houses would become less competitive in the market if they did not provide the conveniences that people require on a daily basis. In contrast, when the number of business establishments reaches a certain level, people are willing to pay a higher price to live near CCUS facilities. This reflects that potential buyers place the greatest importance on convenience in their daily lives. The side effects of having a CCUS project in the vicinity can be mitigated by this measure. Additionally, CCUS projects provide potential benefits to the surrounding community. CCUS facilities can reuse CO_2 in the food industry and for other industrial purposes. An increase in industrial output and activities can potentially increase the local employment rate, as indicated by other energy projects (Moreno & Lopez, 2008; Slattery et al., 2011). The heterogeneity of the CCUS industry reveals that the overall negative impact of CCUS projects on housing prices comes from two industries—ethanol production and fertilizer production, and fertilizer production. Their significant negative impact is comparable to our main findings at approximately 10%.



(a) Heterogeneity of price change based on environmental awareness and business establishments.



(b) Heterogeneity of price change based on the industry of CCUS projects.

Figure 9. Heterogeneity of price change in houses induced by CCUS projects.

3.6 Mechanism analysis

The following analysis examines how air pollution (PM 10 concentration at monitoring station level) and traffic flow (average annual daily traffic at monitoring station level) change after the CCUS operation, which may provide additional insights into the mechanism that leads to the estimated effect on housing prices. Data from monitoring stations allows us to merge each home with the nearest station, thereby providing accurate information about traffic flow and air quality for each home. Model 3 of **Table 7** shows that CCUS projects reduce local traffic by 8.69% on an annual basis. Traffic can be an indicator of local economic activities. Contrary to previous research showing that CCUS industrial investments indirectly create jobs and raise labor incomes (Cheng & Jiang, 2022), our estimates indicate that CCUS operations actually adversely affect local economic development and economic activity, thereby reducing property values. Furthermore, the air quality deteriorates by 4.36%. Consequently, the net decline in housing prices caused by CCUS operations may also be attributed to changes in air pollution, since a worsening air environment is likely to result in a decline in property value.

Regarding the positive impacts on house values within 5 km of CCUS projects, we identify those houses as treatment houses and use the same approach to examine whether local economic developments and air quality differ within a smaller radius. Model 1 indicates that traffic flow decreases by 14.62%, which means that local economic development might be hampered more if CCUS projects are located closer to communities. Model 2 produces a different outcome than the air quality analysis of a 15-km treatment zone. It demonstrates that living within 5 km of a CCUS project reduces the PM 10 concentration by 5.85%. Thus, the positive impact of CCUS projects within 5 km may be attributed to the improvement of air quality. However, such merits might not sustain a broader radius. The low net capture rates due to uncaptured combustion emissions from coal and natural gas have raised concerns that CCUS projects might increase air pollution and overall social costs in comparison to what would otherwise occur without capture (Jacobson, 2019).

Table 7. Impact of CCUS projects on traffic flows and air pollution.

	Treated houses: within 5 km of a CCUS project		Treated houses: within 15 km of a CCUS project	
	ln AADT	*ln* PM 10	*ln* AADT	*ln* PM 10
Model	**1**	**2**	**3**	**4**
D	-0.1462***	-0.0585**	-0.0869*	0.0436*
	(0.0509)	(0.0273)	(0.0525)	(0.0230)
Demographic features control	Yes	Yes	Yes	Yes
Business establishments control	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Month-of-sample FE	Yes	Yes	Yes	Yes
County-by-year FE	Yes	Yes	Yes	Yes
Observations	15422	36589	15422	36589

Notes: AADT: average annual daily traffic. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.7 Event study evidence

Figures 10 and **11** illustrate the coefficients prior to (leads) and following (lags) the operation of CCUS projects based on event study models. Before the operation of CCUS projects, the impacts of CCUS facilities on housing prices are not statistically different from zero. After CCUS operations, negative impacts from CCUS projects on nearby property values start to emerge. **Figures 10** and **11** illustrate that our model can adequately control for time-varying unobservable differences among houses within and outside an oil basin, with or without proximity to CCUS projects before their operation, providing empirical support for the parallel trend assumption.

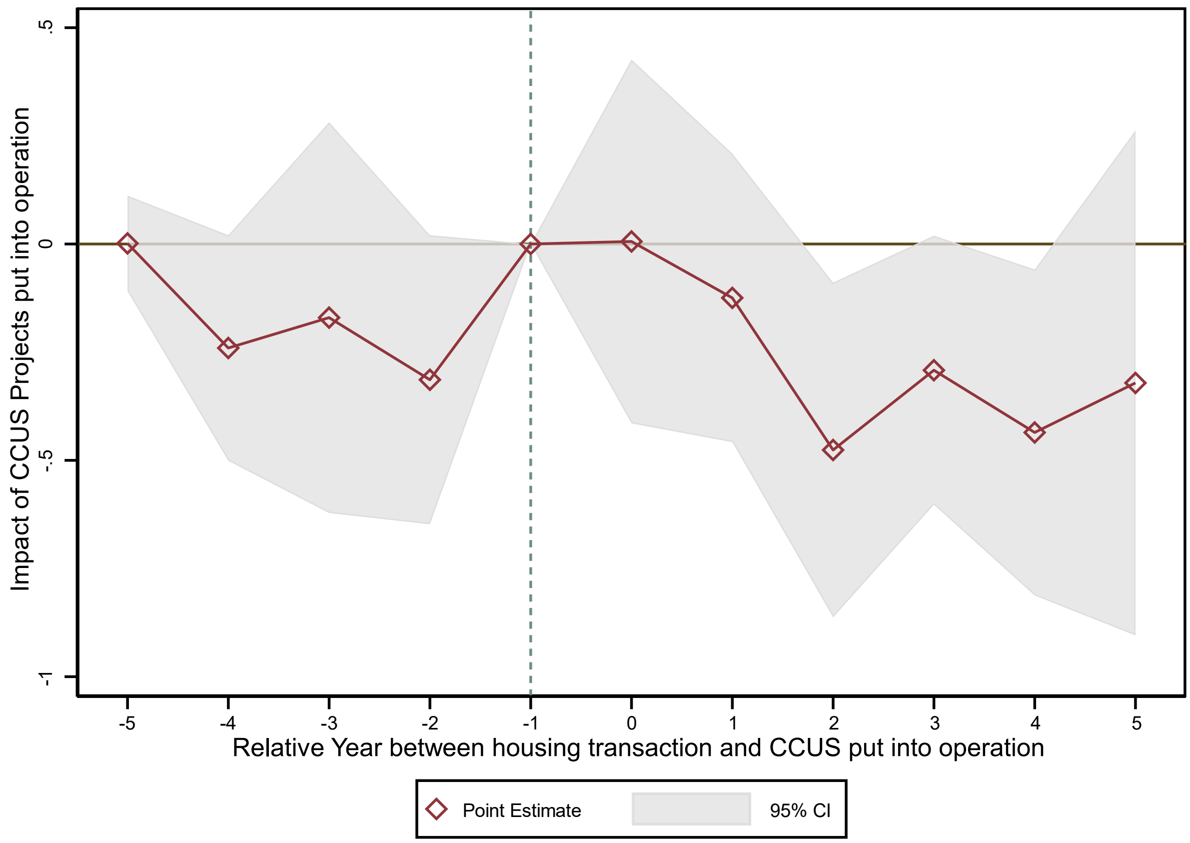


Figure 10. Event study evidence for DID approach. *Notes*: t=-1 is the excluded period. We have dropped the observations prior to t = −5 and following t = 5. The standard errors are clustered by zip code. We include zip-code and county-by-year fixed effects. The number of treated zip codes is 112, and the number of control zip codes is 2,789.

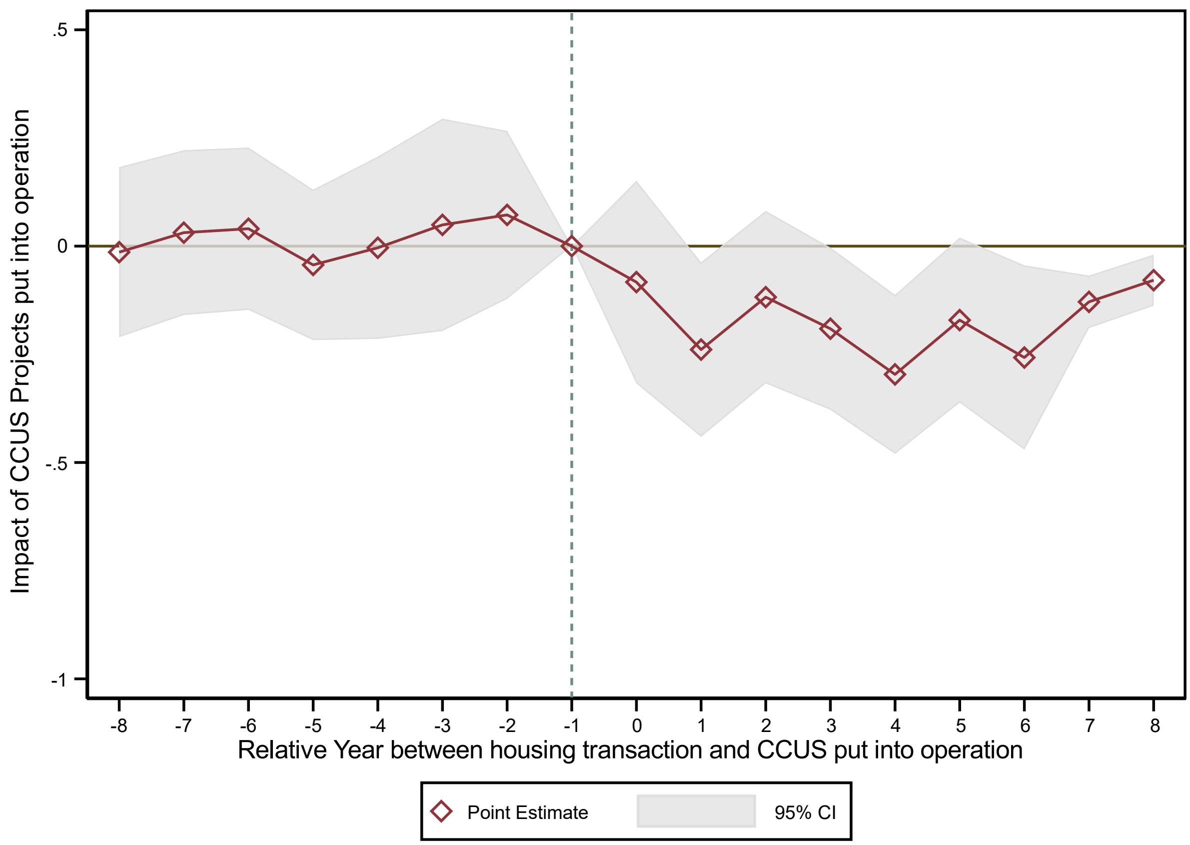


Figure 11. Event study evidence for DDD approach. *Notes*: t=-1 is the excluded period. Observations before t = 8 and after t = 8 have been dropped. The standard errors cluster at the household level. We include individual fixed effects, month-by-year fixed effects, and county-by-year fixed effects. There are 29,996 treated houses for DDD (houses in a basin near a CCUS after its operation) and 2,398,774 control houses.

3.8 DID Robustness check results

Our buffer estimate indicates that the treatment group's boundary is (0, 15] km from the nearest CCUS project, while the control group's boundary is (15, 100] km. To test if our main DID results are sensitive to the 100-km boundary we selected, we decrease the outer boundary of the control group in a range of 30 km to 90 km by a 10-km distance bin. Results in **Table 8** show significant negative coefficients for all outer boundaries of the control group. When the outer boundaries exceed 50 km, the coefficients are approximately 10%, which is consistent with our main findings and indicates the estimated results are robust and are not influenced by the outer boundary we chose.

Table 8. Robustness check changing outer boundary of the control group.

	Outcome: Natural log of home prices (2021$)						
Model	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Outer boundary of the control group	30 km	40 km	50 km	60 km	70 km	80 km	90 km
Coef. Of D (ATT)	-0.0665	-0.0888	-0.1022	-0.1038	-0.0975	-0.1014	-0.1021
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Robust Std Err	0.0085	0.0083	0.0082	0.0082	0.0082	0.0082	0.0082
90% CI	-0.0805	-0.1024	-0.1157	-0.1173	-0.1110	-0.1149	-0.1156
90% CI	-0.0524	-0.0751	-0.0887	-0.0903	-0.0841	-0.0879	-0.0886
R-sq	0.165	0.113	0.103	0.118	0.148	0.158	0.166
Observations	315,667	574,802	922,142	1,360,181	1,911,339	2,503,665	2,988,612
Groups/Houses	129,238	235,147	376,682	553,371	769,750	999,171	1,194,211
Treated houses	85,434	85,434	85,434	85,434	85,434	85,434	85,434
Building age control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business establishments control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-sample FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

4 Discussions and Conclusions

This paper examines the impact of CCUS operations on the value of nearby properties. Based on the buffer we calculated, properties located within 15 km of a CCUS project are considered close to and likely to be affected by CCUS projects. We find that the sale prices fall by 10.18% overall due to CCUS operations. The impact of CCUS facilities on houses within the buffer zone is not monotonic. As distance increases, the impact shifts from a positive impact to a negative impact. Within 5 km of CCUS projects, house values increase by 3.6%. The impact then shifts to being significantly negative and reduces around 10% of property values within a distance of 8 km to 15 km from the nearest CCUS projects. A CCUS project's overall negative impact varies depending on the project type and facility condition. Property values decrease by 9.88% and 6.42% after the operation of a carbon capture and a storage project within 15 km of the property, respectively. Retrofit CCUS projects have no significant impact on nearby housing prices, while new-built CCUS projects significantly reduce the price of nearby houses by 10.68%. Given that being positioned in an oil basin may also affect housing values, our study also uses a DDD approach to distinguish between CCUS effects and oil basin effects on housing prices. We find that the CCUS operation has a net impact of -17.84% on nearby housing prices when compared to similar houses in oil basins without CCUS operations. For robustness tests, we use cross-sectional data along with nearest-neighbor matching. Results support the validity of the estimated negative effects.

CCUS is recognized as one of the essential technologies for attaining low-carbon consumption of fossil fuels in the future as well as a major technical means for maintaining the flexibility of the power system working towards net-zero carbon emissions (IEA, 2021). Our findings have important implications for the successful expansion of CCUS projects on a large scale around the globe. Firstly, our empirical findings expand on the previous discussion of CCUS projects. Through the analysis of high-resolution spatial data of CCUS and daily housing transaction data from 1990 to 2021, this study estimates the net impact of CCUS on nearby housing values across the United States. CCUS operations have a positive impact on houses within a 5-km radius. However, as distance increases, the positive impact diminishes, and adverse environmental costs begin to dominate. Local residents will benefit more if CCUS projects are located closer to their communities. The total impact zone of CCUS projects is 15 km, and our estimation indicates an overall negative impact of CCUS projects on nearby housing prices. As a result, CCUS operations will involve community resilience. DOE is working on building energy hubs, of which CCUS projects are key elements. Whenever energy hubs are built, community resilience should be considered, as should solutions be offered to mitigate any potential negative impacts on the community. This is especially important in light of the ongoing attention to climate justice, in which the potential negative impacts of the adoption of climate mitigation measures on certain groups of consumers should be adequately addressed. Our study helps policymakers understand the potential adverse impacts of CCUS operations on local communities. Policymakers should develop a strategy such as compensation schemes to help mitigate such negative impacts while promoting CCUS projects to enhance climate justice in local communities.

Secondly, we also highlight the disparity between economic benefits and external costs of CCUS projects borne by the surrounding communities. CCUS projects have an impact zone of about 15 km, with a 10.2% reduction in nearby housing prices as a result. We conduct a mechanism analysis to look at how CCUS operations are capitalized into housing prices. Our findings suggest that reduced house prices may be attributed to a decrease in local economic development in general, caused by CCUS operations within 15 km, a departure from prior findings that CCUS investments indirectly create jobs and raise labor incomes (Cheng & Jiang, 2022). Furthermore, the net decline in housing prices caused by CCUS operations may also be attributed to increased air pollution, since a worsening air environment is likely to result in a decline in property values. It is worth considering whether homeowners should be compensated for the loss they have suffered as a result of CCUS developments. Our findings also show that houses located within 5 km of the site have seen an increase in sale prices. Additionally, we examine houses within a 5-km radius of CCUS projects to determine the mechanisms of positive impacts resulting from CCUS. We find that the increase in house prices may be attributed to the implementation of CCUS projects which capture carbon emissions and improve local air quality. Those merits, however, could not be sustained in a wider impact zone (15-km radius), as prior research indicates that the low net captured rates actually lead to an increase in air pollution compared to when there is no capture (Jacobson, 2019). Accordingly, in the siting choices of CCUS projects, it is important to balance the potential damage and the potential benefits to local communities. As retrofitted CCUS projects do not affect nearby property values, future CCUS developments can promote retrofitting the existing facilities. A carbon storage project affects housing prices more adversely than a carbon capture project in new-built projects. Consequently, if a new carbon storage facility is necessary, the site should be located at a greater distance from the local community than a new carbon capture facility.

Thirdly, the heterogeneous impacts of the CCUS project need to be considered and incorporated into policy decisions. We present a comprehensive analysis of heterogeneous responses based on environmental awareness, local economic activities, and the industry of CCUS projects. Our findings indicate that housing prices reduce more in areas with people with average environmental awareness. Consumers with low and high levels of environmental awareness, however, are not affected by the proximity to CCUS projects when purchasing a home. When there are fewer business establishments in areas near CCUS facilities, people are reluctant to live there unless the price of housing is reduced. When the number of business establishments increases to an average level, consumers are willing to pay more for a home even if it is close to a CCUS facility. It is essential for policymakers to conduct a heterogeneous analysis to make an informed choice regarding the location of the facility. Furthermore, the topic of climate justice also raises our concern that the adverse effects of CCUS projects may not be equally distributed among people. The mitigation of CCUS's overall negative impacts should therefore not be monotonous, as CCUS techniques could have had a distinctly different impact on different individuals. Using our findings, we may be able to create compensation plans that are tailored to different individuals. A heterogeneity analysis also reveals that the overall negative impact of CCUS projects on housing prices is primarily attributable to two industries: ethanol production and fertilizer production, and fertilizer production. This significant negative impact is approximately 10% on houses within 15 km. As a result, a CCUS project may be located at a distance of more than 15 km if it involves either ethanol production and fertilizer production or fertilizer production to mitigate negative externalities.

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Supplementary Tables

Table A1. Facility name.

Site	Facility Name
1	Air Products Steam Methane Reformer
2	Arkalon CO2 Compression Facility
3	Bell Creek - Incidental CO2 Storage Associated with a Commercial EOR Project
4	Bonanza BioEnergy CCUS EOR
5	Borger CO2 Compression Facility
6	Century Plant
7	CO2 Sequestration Field Test: Deep Unminable Lignite Seam
8	Coffeyville Gasification Plant
9	Core Energy CO2-EOR
10	Cranfield Project
11	E.W. Brown 0.7 MWe Pilot Carbon Capture Unit
12	Enid Fertilizer
13	Farnsworth Unit EOR Field Project - Development Phase
14	Frio Brine Pilot
15	Fuel Cell Carbon Capture Pilot Plant
16	Great Plains Synfuels Plant and Weyburn-Midale
17	Illinois Basin Decatur Project (CO2 Injection Completed, Monitoring Ongoing)
18	Illinois Industrial Carbon Capture and Storage
19	Kevin Dome Carbon Storage Project - Development Phase
20	Lost Cabin Gas Plant
21	Marshall County ECBM Project
22	MGSC Validation Phase (Phase II): CO2 Storage and Enhanced Oil Recovery: Bald Unit Oil Field Test Site
23	MGSC Validation Phase (Phase II): CO2 Storage and Enhanced Oil Recovery: Sugar Creek Oil Field Test Site
24	Michigan Basin (Phase II) Geologic CO2 Sequestration Field Test
25	Michigan Basin Large Scale Injection Test
26	Mountaineer Validation Facility
27	National Carbon Capture Center (NCCC)
28	NET Power Clean Energy Large-scale Pilot Plant
29	PCS Nitrogen
30	Petra Nova Carbon Capture
31	Plant Barry & Citronelle Integrated Project
32	Pleasant Prairie Power Plant Field Pilot
33	San Juan Basin ECBM Storage Test
34	Shute Creek Gas Processing Plant
35	Terrell Natural Gas Processing Plant (formerly Val Verde Natural Gas Plants)
36	West Pearl Queen CO2 Sequestration Pilot Test and Modelling Project
37	Wyoming Integrated Test Center (ITC)

Note: Facility name for CCUS projects in the United States are provided in Global CCS Institute (https://co2re.co/FacilityData).

Table A2. Information of CCUS projects.

Site	Retrofit	Capture	Storage	community10	Type	Category	Status	Operational	Industry
1	1	1	0	1	capture	Commercial CCS Facility	Operational	2013	Hydrogen Production
2	0	1	0	1	capture	Commercial CCS Facility	Operational	2009	Ethanol Production
3	0	0	1	0	MVA, storage and EOR	Pilot and Demonstration CCS Facility	Operational	2010	Natural Gas Processing
4	0	1	0	1	capture	Commercial CCS Facility	Operational	2012	Ethanol Production
5	0	1	0	1	capture	Commercial CCS Facility	Completed	2001	Fertiliser Production
6	0	1	0	0	capture	Commercial CCS Facility	Operational	2010	Natural Gas Processing
7	0	0	1	0	storage performance test	Pilot and Demonstration CCS Facility	Completed	2009	N/A
8	0	1	0	1	capture	Commercial CCS Facility	Operational	2013	Fertiliser Production
9	0	0	1	1	EOR	Commercial CCS Facility	Operational	2003	Natural Gas Processing
10	0	0	1	1	monitor CO2 injection	Pilot and Demonstration CCS Facility	Operational	2009	N/A
11	0	1	0	1	test carbon capture tech	Pilot and Demonstration CCS Facility	Operational	2014	Power Generation
12	0	1	0	1	capture	Commercial CCS Facility	Operational	1982	Fertiliser Production
13	0	0	1	1	test and monitor CO2 injection	Pilot and Demonstration CCS Facility	Operational	2013	Ethanol Production and Fertiliser Production
14	0	0	1	1	monitor CO2 injection and test storage performance	Pilot and Demonstration CCS Facility	Completed	2004	N/A
15	0	1	0	1	test carbon capture tech	Pilot and Demonstration CCS Facility	Operational	2016	Power Generation
16	1	1	0	1	capture	Commercial CCS Facility	Operational	2000	Synthetic Natural Gas
17	0	1	1	1	bioenergy carbon capture and geological storage (BECCS)	Pilot and Demonstration CCS Facility	Completed	2011	Ethanol Production
18	0	1	1	1	Carbon Capture and Storage	Commercial CCS Facility	Operational	2017	Ethanol Production
19	0	0	1	0	monitor CO2 injection and test storage performance	Pilot and Demonstration CCS Facility	Completed	2014	N/A
20	1	1	0	0	capture	Commercial CCS Facility	Operation Suspended	2013	Natural Gas Processing
21	0	0	1	1	storage performance test	Pilot and Demonstration CCS Facility	Completed	2009	N/A

22	0	0	1	1	CO2 injection test, CO2 Storage and EOR	Pilot and Demonstration CCS Facility	Completed	2009	N/A
23	0	0	1	1	CO2 injection test, CO2 Storage and EOR	Pilot and Demonstration CCS Facility	Completed	2009	N/A
24	1	0	1	1	CO2 Sequestration Field Test	Pilot and Demonstration CCS Facility	Completed	2008	Natural Gas Processing
25	1	0	1	1	CO2 Sequestration Field Test	Pilot and Demonstration CCS Facility	Operational	2013	Natural Gas Processing
26	1	1	1	1	carbon capture, monitor CO2 injection and test storage performance	Pilot and Demonstration CCS Facility	Completed	2009	Power Generation
27	0	1	0	1	test carbon capture tech	Pilot and Demonstration CCS Facility	Operational	2011	Various
28	0	1	0	1	demonstrate new tech of capture	Pilot and Demonstration CCS Facility	Operational	2018	Power Generation
29	0	1	0	1	capture	Commercial CCS Facility	Operational	2013	Fertiliser Production
30	1	1	0	1	capture	Commercial CCS Facility	Operation Suspended	2017	Power Generation
31	1	1	1	1	capture and storage	Pilot and Demonstration CCS Facility	Completed	2012	Power Generation
32	0	1	0	1	test CO2 capture tech	Pilot and Demonstration CCS Facility	Completed	2008	Power Generation
33	0	0	1	1	storage performance test	Pilot and Demonstration CCS Facility	Completed	2008	N/A
34	0	1	0	0	capture	Commercial CCS Facility	Operational	1986	Natural Gas Processing
35	0	1	0	0	capture	Commercial CCS Facility	Operational	1972	Natural Gas Processing
36	0	0	1	0	test storage performance	Pilot and Demonstration CCS Facility	Completed	2002	N/A
37	0	1	0	1	carbon capture test	Pilot and Demonstration CCS Facility	Operational	2018	Power Generation

Notes: Global CCS Institute (https://co2re.co/FacilityData) provides facility name, facility category, facility status, country, operational year, facility industry, and facility short description. Retrofit, capture, storage, community10, and type are collected from ZEROCO2.NO (http://www.zeroco2.no/projects/countries/usa), company websites, and news. The authors created the first column based on the order in which projects are listed in Global CCS Institute. The *retrofit* variable is a dummy variable. It equals 1 if the facility has been retrofitted, and 0 otherwise. Based on the type of project, two dummy variables were created: capture and storage, the information for which was compiled from news articles and company websites. *Capture* equals 1 for carbon capture projects, and 0 otherwise. *Storage* equals 1 for carbon storage projects, and 0 otherwise. *Community10* indicates whether a residential community is within 10 miles of the CCUS project. The value of Community10 is equal to zero if there is no residential community within 10 miles of the CCUS project, suggesting the project is located in rural areas. Otherwise, it is equal to one.

Table A3. DID results clustering standard errors at the county level.

	Outcome: Natural log of home prices (2021$)						
Model	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Project type	All CCUS	Carbon Capture	Carbon Storage	Retrofit CCUS	New CCUS	New Capture	New Storage
Coef. of D (ATT)	-0.1018	-0.0988	-0.0643	0.0420	-0.1067	-0.1037	-0.1313
p-value	0.027	0.043	0.259	0.174	0.019	0.031	0.028
Robust Std Err	0.0459	0.0484	0.0567	0.0305	0.0451	0.0476	0.0590
90% CI	-0.1776	-0.1788	-0.1581	-0.0090	-0.1812	-0.1824	-0.2292
90% CI	-0.0260	-0.0188	0.0296	0.0930	-0.0323	-0.0249	-0.0334
R-sq	0.163	0.175	0.059	0.058	0.170	0.183	0.063
Observations	3,585,195	3,318,293	459,843	168,244	3,416,951	3,154,147	312,633
Groups/Houses	1,438,093	1,326,630	198,625	76,221	1,379,157	1,252,324	132,179
Treated houses	85,434	77,495	23,935	4,199	81,235	74,039	21,407
Building age control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business establishments control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-sample FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors are clustered at the county level. The outcome is the natural log of home prices that are adjusted to 2021$ for inflation. During the post-treatment period, the treated buildings were traded with a CCUS project nearby. Transactions with the treatment (having CCUS projects within 100 km) happened from 1990 to 2021.

Table A4. DDD robustness check: changing the boundary of basin control group

	Outcome: Natural log of home prices (2021$)									
Boundary of basin control group	10 km	20 km	30 km	40 km	50 km	60 km	70 km	80 km	90 km	100 km
Coef. of DDD	-0.178	-0.178	-0.178	-0.178	-0.178	-0.178	-0.178	-0.178	-0.178	-0.178
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Robust Std Err	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032
90% CI	-0.232	-0.232	-0.232	-0.232	-0.232	-0.232	-0.232	-0.232	-0.232	-0.232
90% CI	-0.125	-0.125	-0.125	-0.125	-0.125	-0.125	-0.125	-0.125	-0.125	-0.125
R-sq	0.259	0.259	0.259	0.259	0.259	0.259	0.259	0.259	0.259	0.259
Obs					2,646,882					
Building age control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business establishments control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-sample FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Supplementary figures

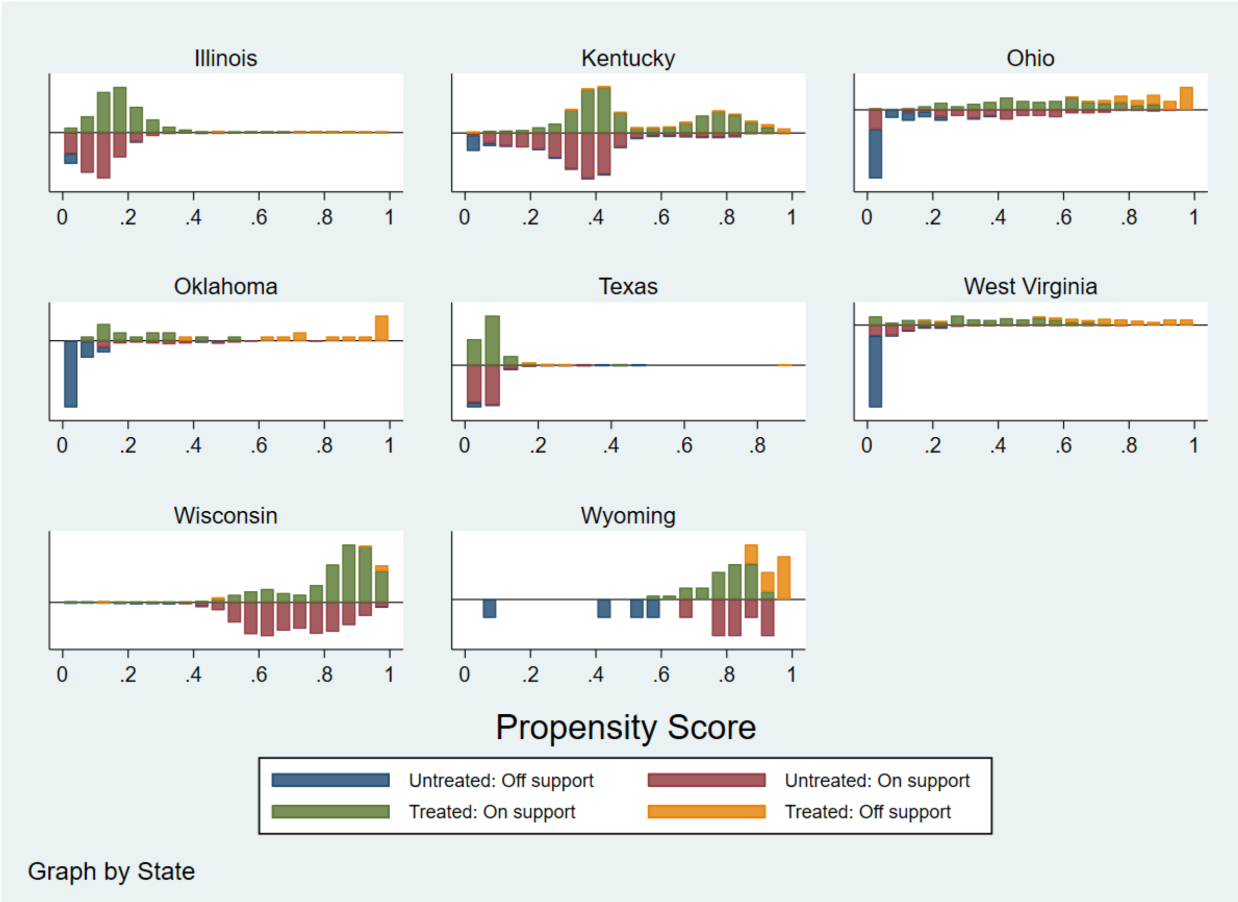

Figure A1. Common support for matching the houses with nearby CCUS projects and those without.