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ABSTRACT

Carbon capture, utilization, and storage (CCUS) techniques are vital to decarbonization goals. A CCUS supply chain captures CO_2 and delivers it to a suitable location where CO_2 can either be used or injected deep underground for long-term storage. CCUS projects reduce carbon emissions but also pose certain risks to local communities. Using nationwide CCUS data combined with property-level transaction records from 1990 to 2021 in the U.S., we quantify the net impact of proximity to CCUS projects on nearby housing prices in light of their positive and negative externalities. The results show that proximity to CCUS projects leads to a price premium on nearby house sales prices, but such effects disappear beyond the 4.2-km buffer. Compared to homes without CCUS projects nearby, houses with CCUS projects within 4.2 km typically command a price premium of 3.90% (or $8,582). CCUS deployment could be facilitated with a more detailed explanation of the housing price premium. The observed increase in property values near CCUS operations in the U.S. provides insights that could inform CCUS project development in other regions, though local regulatory and socio-economic factors must be carefully considered.

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A data appendix is available at http://www.nber.org/data-appendix/w32713

Introduction

Carbon capture, utilization, and storage (CCUS) integrates several techniques to reduce CO_2 emissions in the atmosphere. As part of the CCUS supply chain, CO_2 is captured from stationary sources, compressed, transported, and transformed into useable products or injected deep underground for long-term storage, which effectively reduces carbon dioxide emissions into the atmosphere (see **Fig. 1**).

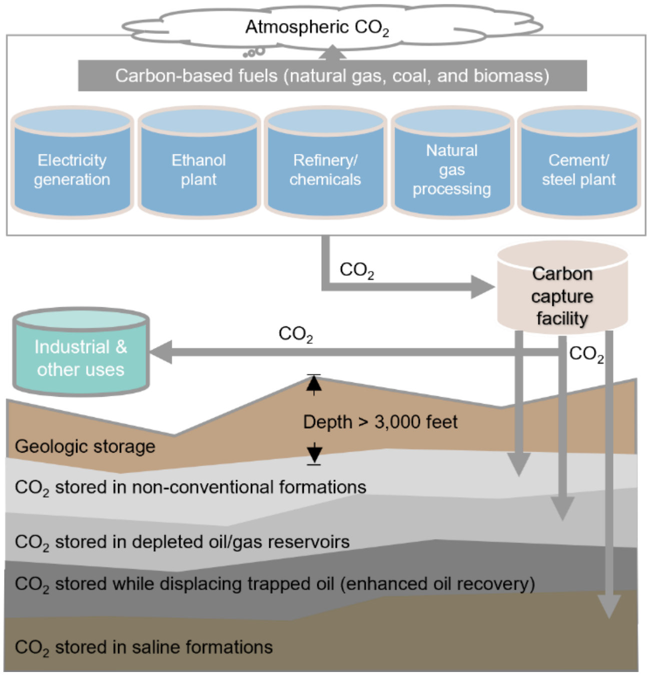

Fig. 1. The supply chain for carbon capture, utilization, and storage projects[1].

CCUS is widely regarded as a crucial technology for achieving carbon neutrality by mid-century (Chen et al., 2022; Duan et al., 2021). However, there is an ongoing debate about its optimal role in transitioning to a low-carbon future. Critics of CCUS raise several concerns. Studies suggest that directly replacing fossil fuel plants with renewable energy sources is more effective in reducing both CO_2 and air pollution emissions (Jacobson, 2019), while also offering higher net energy returns compared to CCUS technologies (Sgouridis et al., 2019). Additionally, there are apprehensions about the long-term safety of CO_2 storage (Zoback & Gorelick, 2012) and the equitable distribution of local risks associated with CCUS projects (Witt et al., 2020; Shaw et al., 2015). Ethical concerns have also been raised about burdening future generations with large quantities of sequestered CO_2 (Mabon & Shackley, 2015). These considerations underscore the need for a comprehensive assessment of CCUS technologies, carefully weighing their potential benefits against possible drawbacks and alternative solutions.

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[1] DOE. Meeting The Dual Challenge: A Roadmap to At-Scale Deployment of Carbon Capture, Use, and Storage. https://www.energy.gov/sites/default/files/2022-10/CCUS-Tech_Intro-030521.pdf.

As of June 2024, there are 28 operational CCUS projects in the U.S., with an additional 8 under construction[2]. While CCUS projects have experienced rapid development, there are few studies quantitatively assessing the economic costs and benefits of these initiatives within local communities, which poses significant challenges when making pertinent policy decisions concerning the expansion of CCUS projects.

The environmental and economic benefits of CCUS projects are multifold. CCUS can reuse CO_2 for enhancing oil recovery (EOR) and coal bed methane recovery and for the food industry and other industrial applications, which can potentially increase the local employment rate and economic activities as suggested by other types of energy projects (Moreno & López, 2008; Slattery et al., 2011). The presence of CCUS projects could drive local economic growth and benefit nearby communities through increased employment opportunities (Chen & Jiang, 2022). CCUS technology presents a dilemma in the transition to clean energy. On one hand, it can extend the operational life of coal-fired power plants and allow fossil fuel-rich countries to utilize their existing assets while reducing CO_2 emissions (Johnsson et al., 2019). On the other hand, this approach raises significant concerns. Critics argue that CCUS should not be used to prolong the life of avoidable fossil CO_2 sources (Mertens et al., 2023) as CCUS may extend the presence of local air pollutants and could divert resources from the development of renewable energy sources (Jacobson, 2019; Sgouridis et al., 2019). Moreover, investing in CCUS rather than renewables consistently leads to higher total social costs, including increased health impacts from air pollution (Jacobson, 2019). This situation highlights the challenging balance between short-term economic considerations and long-term environmental and health priorities in CCUS deployment. While the technology may offer a transitional solution in the shift towards cleaner energy, it also raises questions about the pace and direction of this transition.

While the benefits of carbon sequestration are accrued globally by reducing the level of CO_2 emitted to the atmosphere, the potential negative externalities of CCUS projects mostly fall disproportionately on local communities. For example, a CCUS project may pose risks to nearby geological formations and thus increase the probability of complications such as earthquakes (Zoback & Gorelick, 2012, 2015). CO_2 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). The energy penalty associated with CCUS in power plants also exists by increasing air pollution (EEA, 2011; Jacobson, 2019). Concerned individuals have established a website entitled "Citizens Against CO2 Sequestration[3]". Thus, local communities are aware of the negative externalities of CCUS projects. However, it is difficult to accurately

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

[3] Citizens Against CO2 Sequestration. https://citizensagainstco2sequestration.blogspot.com/. Supplementary Figure 1 presents a screenshot for the website.

quantify these geological and pollution risks and the impact of such risks on local communities due to the lack of data and rigorous empirical evidence.

As noted by Rosen (1974), the hedonic price model is a well-established revealed preference approach for non-market valuation. This method allows us to infer the value that individuals place on environmental amenities or disamenities, such as perceived CCUS risks, through their housing choices. In addition, we have access to detailed, individual-level housing transaction data, which provides a high level of temporal and spatial resolution. This granularity allows us to more accurately capture local effects that might be missed in aggregate measures. While other indicators such as employment levels or GDP per capita are valuable, these aggregate measures often lack the fine-grained temporal and spatial resolution needed to isolate the specific impacts of CCUS projects on local communities.

To contextualize our study within the broader framework of decarbonization and the built environment, it is crucial to consider the evolving role of CCUS technologies in urban and residential settings. Recent literature highlights the significant potential of CCUS in reducing emissions from energy-intensive industries (Fennell et al., 2022), which are crucial for urban development and infrastructure. Our focus on CCUS projects near residential areas is particularly relevant given the increasing consideration of CCUS deployment in diverse geographical contexts. While not all CCUS projects are located near urban centers, there is growing interest in understanding the implications of CCUS infrastructure on nearby communities (Gough et al., 2018). This raises important questions about the impacts of these industrial facilities on local areas, including effects on property values, local economies, and public perception.

The success of CCUS implementation in or near residential areas heavily depends on public acceptance. L'Orange Seigo et al. (2014) emphasize the critical role of public perception and acceptance in the deployment of CCUS technologies. Our study contributes to this discourse by examining how the presence of CCUS projects is reflected in local housing markets, potentially offering insights into the community valuation of these facilities. By examining the relationship between industrial CCUS projects and nearby housing prices, our study provides valuable insights into the complex interplay between decarbonization efforts and the built environment. These findings can inform policy decisions and urban planning strategies as communities seek to balance climate mitigation goals with local economic and social considerations.

In light of the positive and negative externalities associated with CCUS projects, it is important to determine how the net impact of such projects is perceived through housing markets in the U.S. Using high-resolution spatial data, we provide novel empirical evidence on how potential economics, 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. Our results show that CCUS projects have an impact zone of 4.2 km, beyond which they have no impact on nearby housing prices. The net impact of CCUS projects causes a price premium on housing prices—the sale price increases by 3.90% (or $8,582) on average after CCUS operations.

We make two primary contributions to the economic impact of renewable energy infrastructure. 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; Zabel & Guignet, 2012; Liang et al., 2023). Hewitt and Hewitt (2012) find that houses near urban rail stations are more expensive than those further away. 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 & Guignet, 2012). Similarly, shale gas development (Muehlenbachs et al., 2015) and the conversion of coal-fired power plants into gas-fired ones (Mei et al., 2021) all potentially reduce 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 these projects could lead to a decrease in house values (Dröes & Koster, 2016; Gibbons, 2015) due to factors such as blocking of views, noise from wind turbines, and Nimbyism. Secondly, our paper adds to the strand of literature that examines public attitudes toward CCUS projects by revealing preferences in the United States. Liu et al. (2021) and Linzenich et al. (2019) examined public perceptions of CCUS projects in China and Germany, respectively, based on the survey approach. There is conflicting evidence regarding how individuals value CCUS projects (Sun et al., 2020). Our study provides valuable insights into how CCUS projects may be expanded efficiently, as possible opposition from residents could lead to increased tensions, similar to the resistances observed during wind and solar project expansion (Carlisle et al., 2015). Our findings have important implications for the successful implementation of CCUS projects in the United States and can serve as a useful starting point for policymakers and researchers in other regions considering CCUS deployment, providing a framework for evaluating potential impacts and public responses.

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 coarsened exact matching. Furthermore, we analyze the heterogeneous treatment effects of CCUS projects concerning the environmental awareness and industry of CCUS projects. Our event study evidence indicates that our treatment and control groups had comparable trends before the treatment. Details of the models and data can be found in Methods.

Defining the buffer

Our analysis using local polynomial regression reveals the extent of CCUS facilities' influence on nearby property values. **Fig. 2** illustrates the relationship between housing price residuals and distance from CCUS facilities.

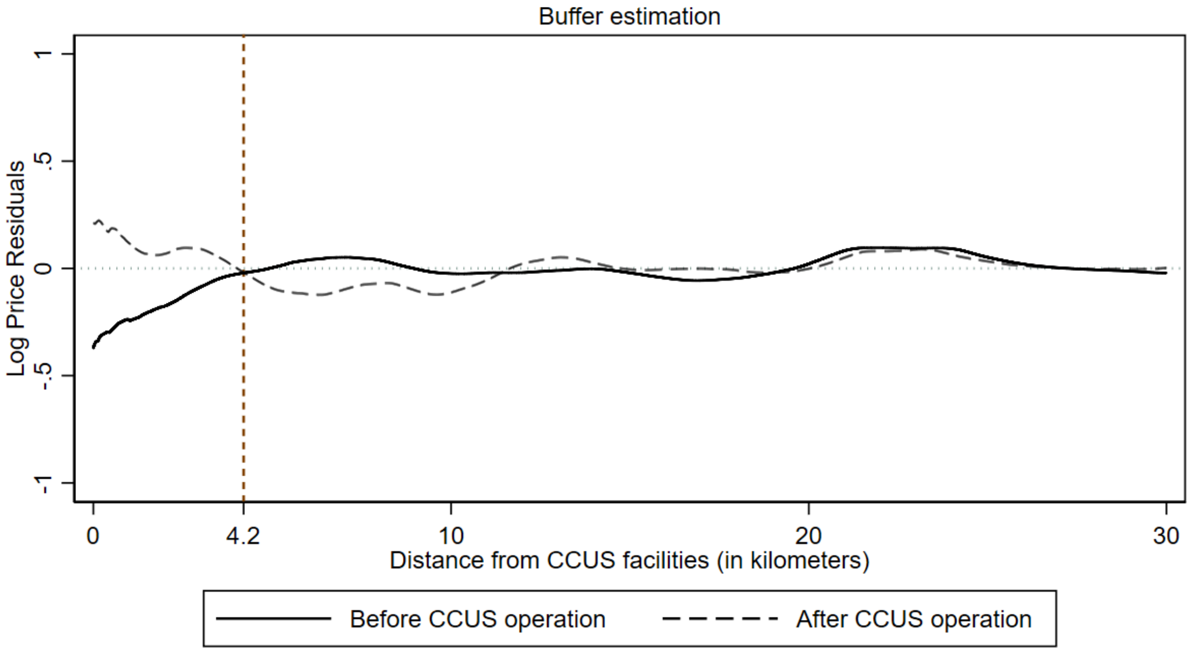

Fig. 2. Price Gradient of Distance from CCUS facilities. In DID estimation, houses that are "close" to CCUS projects will be considered treatment houses. A buffer estimation identifies what is considered "close". The vertical axis presents the residuals of the log housing price, which is defined as price residual = actual housing prices – predicted housing prices. The predicted value is calculated using a local polynomial regression model based on the building characteristics. CCUS residuals beyond 4.2 km of a project are both close to zero, meaning that based on building features, predicted housing prices are not significantly different from actual housing prices. However, within 4.2 km, both residuals significantly deviate from zero, indicating that building characteristics no longer accurately predict the sales prices of houses within 4.2 km of CCUS projects. Accordingly, CCUS projects affect the sales price of houses within 4.2 km of the project. Thus, the buffer is 4.2 km.

For properties beyond 4.2 km from CCUS sites, price residuals remain close to zero both before and after facility operation. This indicates that building characteristics alone can accurately predict housing prices in these areas. However, within a 4.2 km radius, price residuals deviate significantly from zero, suggesting that proximity to CCUS facilities affects property values beyond what building features alone would predict. This 4.2 km threshold defines our "buffer zone" for assessing CCUS impacts on housing prices. Within this zone, we observe distinct patterns in price residuals before and after CCUS operations begin.

CCUS operations appear to positively impact nearby housing prices. Analysis indicates that actual housing prices exceed predicted values after CCUS projects begin, suggesting these initiatives bring net economic benefits to the surrounding area. This may be attributed to potential economic benefits associated with CCUS projects, such as increased employment opportunities (Chen & Jiang, 2022). However, the environmental impacts of CCUS are more context-specific. The overall effect of CCUS on air quality and other environmental aspects varies depending on factors such as the particular technology employed, the CO_2 source, and the ultimate use of the captured carbon (Cuéllar-Franca & Azapagic, 2015). CCUS technologies have the potential to reduce certain pollutants compared to conventional alternatives in some instances. However, it is important to note that environmental benefits are not guaranteed across all CCUS applications (von der Assen et al., 2013). Some CCUS technologies may increase emissions of other substances, such as ammonia (Veltman et al., 2010). Despite these environmental uncertainties, the positive residuals in housing prices within a 4.2 km radius of CCUS operations indicate that the perceived economic advantages outweigh potential drawbacks in the minds of homebuyers and the local real estate market. This suggests a generally favorable view of CCUS projects among nearby residents, at least as reflected in property values.

Interestingly, before CCUS operations begin, price residuals are negative, suggesting lower-than-expected housing prices. This could stem from community concerns about potential risks associated with planned CCUS facilities. Supplementary Figure 1 indicates that citizens are aware of the negative externalities associated with CCUS projects, including increased earthquake risks (Zoback & Gorelick, 2012, 2015) and water pollution (Newmark et al., 2010). Local communities bear a majority of these negative externalities, which may lead to a decline in housing prices when citizens are informed about a planned CCUS facility nearby.

It is important to note that we cannot directly compare the sales prices of nearby properties before and after CCUS operations, as the price residuals are calculated based on different predicted models using separate datasets.

In our main model, we assess the CCUS impacts on treated versus control houses using the 4.2 km as the treatment buffer. As an additional exploration of the changes in the impact of CCUS projects after operations, we also conduct a distance bin analysis in a 1 km increment within the 4.2 km buffer zone.

Price premiums vary with distance

Our study examines how carbon capture, utilization, and storage (CCUS) projects affect nearby housing prices. We use a two-way fixed effects model (or a generalized DID model) to analyze housing transactions within 30 km of CCUS projects. Houses within 4.2 km are considered "treated" by the projects, while those between 4.2 km and 30 km serve as the control group (see **Fig. 3**).

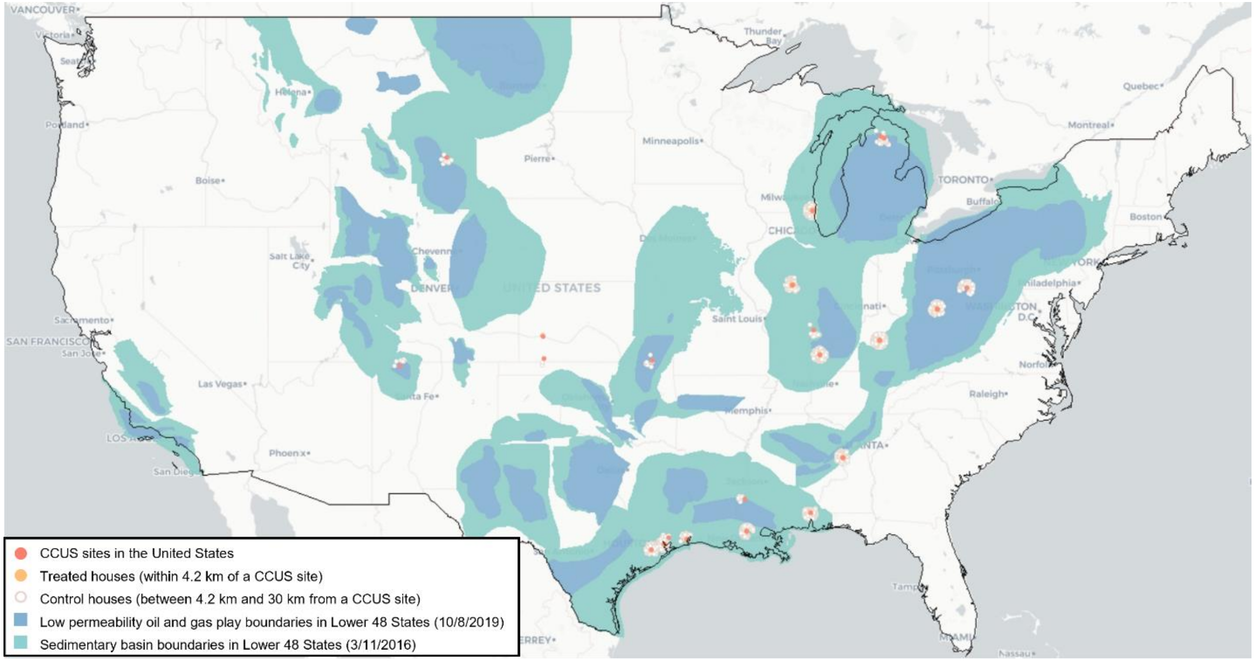

Fig. 3. DID design: the treatment and control houses for CCUS projects, along with boundaries of oil/gas fields and basins. There are 10,705 house transactions close to CCUS projects within 4.2 km and 545,233 transactions without proximity to CCUS projects.

Fig. 4 reveals that proximity to CCUS projects generally increases house sale prices. On average, houses within 4.2 km from a project see a price premium of 3.90% (or $8,582) when accounting for county-specific yearly trends and demographic factors. Interestingly, the price effect varies with distance. Houses closest to the facilities (within 3 km) show no significant price increases. This may reflect a balance between the projects' benefits and potential concerns about potential geological change (Zoback & Gorelick, 2012, 2015) and water pollution (Eldardiry & Habib, 2018). The positive price impact becomes more pronounced at distances between 3 and 4.2 km from the projects. Our regression analysis, detailed in **Table 1**, shows that controlling for county-specific yearly trends (county-by-year fixed effects) produces smaller estimated price premiums compared to using broader yearly trends (year fixed effects). This suggests the importance of accounting for local economic conditions when assessing the impact of CCUS projects.

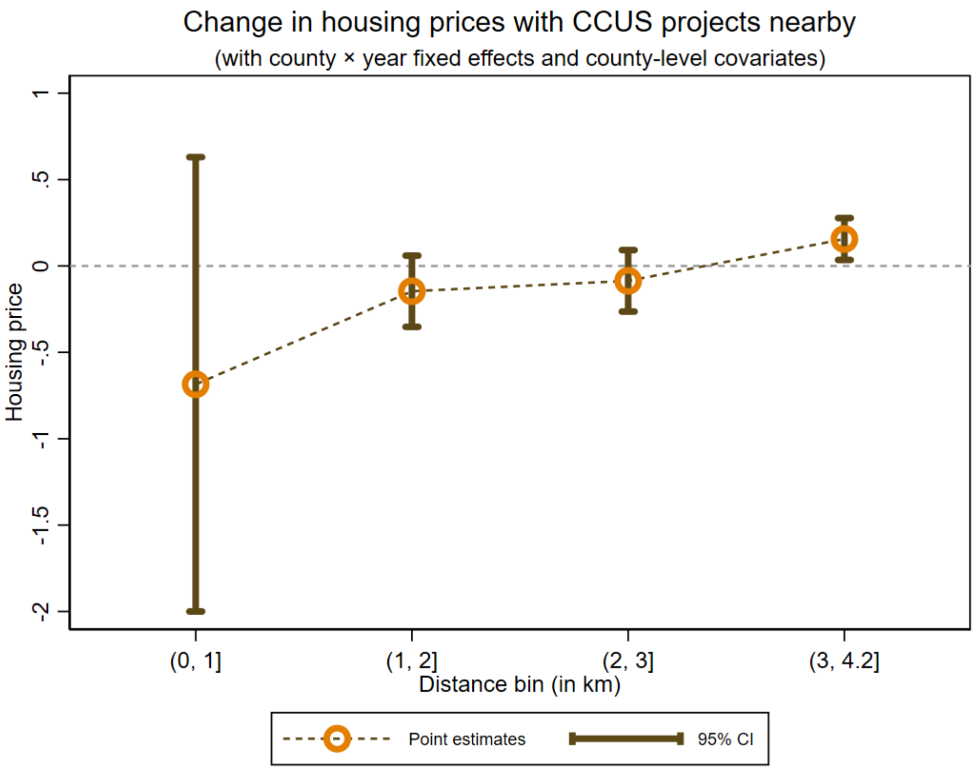

Fig. 4. Impacts of proximity to CCUS projects on housing prices. This figure illustrates the housing price premiums from CCUS impacts with individual, county-by-year, month-by-sample fixed effects, and county-level demographic covariates (column 2 of **Table 1**). The dependent variable is the natural log of house sales prices in 2021 dollars. The label of a tick represents the range of a 1-km distance bin. The error bars are centered on the coefficients, representing point estimates from the regressions. Vertically plotted bars are their 95% confidence intervals. The robust standard errors clustered at the household level. There are 264,318 observations in total for the regression analysis.

Table 1. The impact of CCUS projects on nearby houses' prices by vicinity.

	Outcome: Natural log of home prices (2021$)	
	Year FE	County-by-year FE
Average housing price premium	8.37%	3.90%
Vicinity 0 – 1 km	-0.3710	-0.6851
	(0.6546)	(0.6708)
Vicinity 1 – 2 km	0.0165	-0.1464
	(0.1029)	(0.1053)
Vicinity 2 – 3 km	0.0799	-0.0861
	(0.0901)	(0.0908)
Vicinity 3 – 4.2 km	0.3346***	0.1560*
	(0.0608)	(0.0618)
Observations	264,318	264,318
R-sq	0.179	0.243
Building age control	Yes	Yes
Covariates	Yes	Yes
Property FE	Yes	Yes
Month-by-sample FE	Yes	Yes
Year FE	Yes	No
County-by-year FE	No	Yes

Note: The dependent variable is the natural log of home prices adjusted for inflation to 2021 dollars. Standard errors are in the parentheses. *p<0.05, **p<0.01, *** p<0.001. Robust standard errors cluster at the household level. The transactions in this sample took place between 1990 and 2021, involving houses within 30 km of the CCUS projects. During the post-treatment period, treated households were traded with an adjacent CCUS project. The vicinity coefficients interact with the post-operation dummy variable. The "Average housing price premium" is calculated by averaging the non-omitted coefficients for housing price change across all properties within 4 distance bins. When county-level covariates of personal income and population density are included in column (2), the average housing price premium for houses from CCUS is 3.90%.

In conclusion, our results indicate that CCUS projects generally have a positive effect on nearby property values, but this effect varies with distance. The most substantial benefits appear to occur at a moderate distance from the facilities, balancing the projects' advantages against potential local concerns. To verify our findings, we conduct additional analysis using repeat sales data (i.e., houses that sold more than once during our study period, at least once before and once after the operation of the nearest CCUS project). This approach yielded similar results, supporting the robustness of our main findings. Detailed results can be found in Supplementary Note 3. Given the potential selection bias and sparseness issues with the repeat sales sample, we present the results using the full sample as our main findings and include the repeat sales results as a robustness check.

Cross-sectional results with coarsened exact matching

To further validate our findings, we employ a matching approach to ensure comparability between houses near CCUS facilities (treatment group) and those without nearby facilities (control group). For each treated house, we find a control house comparable on building covariates, sold in the same transaction year, and located in the same county. We then match the treatment and control group based on building characteristics such as building age, total rooms, total bedrooms, area, and number of stories. After matching, we apply the same Difference-in-Differences (DID) framework to this matched sample of 34,153 transactions, considerably smaller than our full sample. Supplementary Table 3 provides a detailed comparison between our main results and those obtained from this combined cross-sectional matching and DID analysis. The results reveal a 3.24% premium in sales price for houses near CCUS facilities, closely aligning with our main findings.

Heterogeneity

The price premiums associated with CCUS projects may vary by industry and socio-economic characteristics. Our study examines how price premiums vary by environmental awareness level and by the industry of the CCUS project. 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. We estimate the non-linear relationship between environmental awareness and the price impact of CCUS projects using a local linear regression on residuals from covariates. **Fig. 5** displays the resulting estimate of $g(U_{iy})$.

Environmental awareness data, measured as the percentage of residents believing in global warming (2020), comes from the Yale Program on Climate Change Communication[4]. **Fig. 5a** reveals a U-shaped relationship between environmental awareness and CCUS price impact, indicating higher price premiums associated with both low and high levels of environmental awareness.

While we lack direct data on individuals' attention to CCUS during property transactions, existing literature suggests that those with higher environmental awareness (more informed about climate change issues) tend to be more familiar with CCUS technology (Li et al., 2017). The higher level of environmental awareness may influence their willingness to pay higher prices for homes near CCUS projects. Previous research has demonstrated that environmental awareness positively affects people's willingness to pay premium prices for environmental benefits, such as renewable electricity (Guo et al., 2014). We propose that this same principle may apply to CCUS projects, with environmentally aware buyers potentially viewing proximity to these facilities as a positive factor in their housing decisions.

Conversely, individuals with lower environmental awareness might not explicitly notice or consider the environmental benefits or risks of CCUS projects when making housing decisions. However, they may be attracted to the potential economic gains associated with large-scale industrial and energy projects, such as increased job opportunities and local economic growth. While some of the economic benefits generated by CCUS projects may be capitalized by the companies operating the facilities, existing literature in labor and industrial economics suggests that large-scale industrial and energy projects often generate positive spillover effects on local economies, extending beyond the direct benefits to the companies involved. For instance, Moretti (2010) found that the opening of a large manufacturing plant can create a multiplier effect on local employment, generating additional jobs in the local service sector. Greenstone et al. (2010) demonstrated that such openings can lead to increased productivity in nearby existing plants, indicating positive agglomeration effects. The energy sector also shows significant local economic impacts. Black et al. (2005) observed that the 1970s coal boom led to increased employment in local sectors beyond mining. Weber (2012) found that the U.S. natural gas boom resulted in significant increases in local employment, wages, and economic activity in affected counties. We hypothesize that CCUS projects may have similar effects, with some economic benefits accruing to local communities. Thus, even those less environmentally aware might value proximity to CCUS projects for economic reasons, even if they are not fully aware of the specific technology involved.

The heterogeneity of the CCUS industry reveals that the overall positive impact of CCUS projects on housing prices comes from two industries—fertilizer production and synthetic natural

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[4] Yale Program on Climate Change Communication. https://climatecommunication.yale.edu/visualizations-data/#visualizations-data-search-filter.

gas (**Fig. 5b**). Their significant positive impact is comparable to our main findings at approximately 20%.

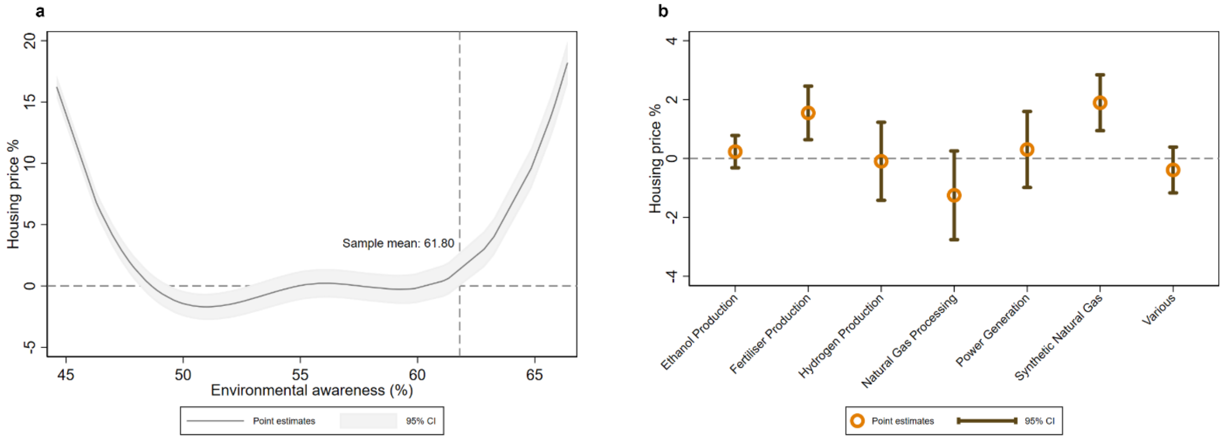

Fig. 5. Heterogeneity of price change in houses induced by CCUS projects. a, Environmental awareness, **b**, Industry of CCUS projects. In each panel, there is a single regression at the house level using the partially linear varying coefficient fixed effects panel data. The centers of the error bands (gray solid line in **a**, orange hollow circle in **b**) indicate the semiparametric estimation of the average effects of the variable on the X-axis. Grey-shaded areas in **a** and olive bars in **b** represent 95% confidence intervals.

Event study evidence

Our event study analysis serves to verify the parallel trend assumption in our difference-in-differences model. We examine the coefficients before (leads) and after (lags) CCUS operations at the household level, as shown in Supplementary Figure 2.

The results confirm the parallel trend assumption between control and treated houses. Before CCUS operations, the effects are not statistically different from zero. Supplementary Figure 2 demonstrates that our model effectively controls for time-varying unobservable differences between houses near and far from CCUS projects, both before and after their operation. This provides empirical support for the parallel trend assumption underlying our difference-in-differences approach.

Interestingly, while not statistically significant before the treatment, we observe a notable upward trend in point estimates leading up to the treatment year. This pattern may suggest the presence of anticipation effects. Given that CCUS projects typically take 2-5 years from announcement to operation, it is plausible that local housing markets begin to react before our defined treatment year (the operational year). These potential anticipatory responses could be driven by factors such as expectations of job creation, as noted by Chen & Jiang (2022). However, the lack of statistical significance in pre-treatment estimates indicates that these effects, if present, are not strong enough to be definitively captured in our current analysis.

Further research with more granular data on project timelines and local economic indicators would be necessary to fully characterize these anticipation effects.

DID robustness checks

In addition to using the repeat sales sample with 0.2 km distance bins, we conduct several robustness checks to strengthen our conclusion that CCUS projects positively impact nearby housing prices across various contexts and analytical approaches.

First, we address the potential bias arising from CCUS projects' proximity to existing industrial facilities. Since CCUS projects are typically located near CO_2 sources like power plants, we create a new control group using similar industrial sites without nearby CCUS projects. This analysis, detailed in Supplementary Note 4, supports our original conclusion, demonstrating a positive impact of CCUS projects on nearby housing prices even when controlling for existing industrial facilities.

Second, we examine the effect of non-disclosure states, where real estate transactions are not publicly recorded, potentially leading to less reliable data. We conduct an analysis excluding five non-disclosure states from our sample: Kansas, Mississippi, Texas, North Dakota, and New Mexico. The results, presented in Supplementary Note 5, remain consistent with our main analysis, indicating that our conclusions are not sensitive to the inclusion or exclusion of these states.

Third, we consider the potential cumulative effect of multiple CCUS projects nearby. Our analysis reveals several CCUS project sites within 60 miles of each other. We introduce a variable indicating the number of CCUS projects nearby. The results, detailed in Supplementary Note 6, show that additional nearby CCUS projects are associated with increased housing prices, further supporting our main findings.

Lastly, we test the sensitivity of our results to the outer boundary of the control group. We vary this boundary from 10 km to 50 km in 10-km increments, using the same difference-in-differences approach with repeat sales sample and 0.2-km distance bins as Supplementary Note 3. Only households that have been sold twice are included in the repeat sales sample, and smaller distance bins can measure changes more thoroughly. All variations show similar patterns to our main findings, as presented in Supplementary Table 4.

Excluding the effect of pandemic

The pandemic ushered in many simultaneous changes in real estate and the emitting industries. For example, a sharp drop in ethanol production in the United States has been observed in 2020[5]. We thus remove transactions occurring during the pandemic starting on March 11, 2020, when

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[5] U.S. fuel ethanol production and inventory changes have largely followed motor gasoline. EIA. https://www.eia.gov/todayinenergy/detail.php?id=44015.

the World Health Organization declared COVID-19 a pandemic[6]. Our goal is to determine if our results may be skewed by the combination of higher home sale prices and potential reduction in emissions resulting from the pandemic. Our full sample, which excludes houses remodeled after 2000, includes 38,758 transactions between March 11, 2020, and December 31, 2021 (the last transaction in the sample). House transactions during the pandemic are excluded because they are likely to be distorted by higher home sales prices and emission reductions during that period. Supplementary Figure 3 shows that price premiums without pandemic influence are also observed after 3 km, and the average price premium within 4.2 km is 3.90%, which is similar to our main findings.

Discussion

This study estimates the capitalization effects of CCUS projects on nearby properties. We find that CCUS projects significantly impact nearby housing prices. This effect disappears beyond 4.2 km. The average price premium for houses within this buffer zone is 3.90% or $8,582. Interestingly, the houses closest to CCUS facilities (within 3 km) do not show significant price increases, suggesting that home buyers may be willing to pay more for proximity to a CCUS facility but may not be willing to live too close to it. Nimbyism is also present in CCUS projects similar to wind power and other green technologies. In addition, no significant effect observed within 3 km can also be explained by concerns about geological change (Zoback & Gorelick, 2012, 2015) and water pollution (Eldardiry & Habib, 2018), which may cancel out the economic advantages delivered by CCUS projects.

The CCUS process generally involves capturing CO_2 emissions at their sources, transporting the emissions to a suitable storage site, and storing them underground or reusing them for industrial purposes. It is also recognized as an essential technology for achieving carbon neutrality by mid-century (Chen et al., 2022). We observe a net positive effect of CCUS projects, which could be attributed to several reasons. CCUS technologies have the potential to reduce certain pollutants compared to conventional alternatives in some instances. However, the overall effect of CCUS projects on air quality is context-dependent, which varies depending on factors such as the particular technology employed, the CO_2 source, and the ultimate use of the captured carbon (Cuéllar-Franca & Azapagic, 2015). Environmental benefits are not guaranteed across all CCUS applications (von der Assen et al., 2013). Some CCUS technologies may increase emissions of other substances, such as ammonia (Veltman et al., 2010).

Our observed net positive effect suggests that, on average, the perceived benefits of CCUS projects outweigh potential negative impacts in local communities. However, our analysis does not directly measure air quality changes or health outcomes. The perceived benefits might stem from a combination of factors, including potential air quality improvements, economic benefits, or other local considerations. Further research on air quality and health impacts of different

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[6] WHO declares novel coronavirus outbreak a pandemic. CNN. https://www.cnn.com/2020/03/11/health/coronavirus-pandemic-world-health-organization/index.html.

CCUS technologies in various contexts would be valuable to fully understand these effects and their contribution to community well-being.

Our findings have important implications for the expansion of CCUS projects on a large scale. First, the buffer zone estimate of 4.2 km and the absence of significant price premiums within 3 km may be critical factors in determining the appropriate location for CCUS projects. The influence of CCUS projects diminishes beyond 4.2 km. Thus, CCUS projects located between 3 and 3.8 km away from the local community can reduce the risk of geological impacts in the surrounding regions and ensure that local communities can reap the net benefits of such projects.

Second, policymakers can utilize the price premium to convince the real estate industry and residents to adopt more CCUS initiatives. Public resistance to CCUS projects has increased due to concerns about water pollution and induced seismicity, as evidenced by online opposition (see Supplementary Figure 1). Public opposition to CCUS projects has been documented in various contexts. For instance, the Barendrecht case in the Netherlands demonstrates how public opposition can lead to project cancellation (Terwel et al., 2012). Perceived risks and benefits, trust in the project initiator, and concerns about local decision-making all played roles in the Barendrecht opposition. In the U.S., CCUS projects have faced both opposition and acceptance depending on local context and social factors (Bradbury et al., 2009). Through focus group interviews conducted across states in the U.S., Bradbury et al. (2009) discovered that social issues often overshadow concerns about the technology itself. These social factors include skepticism towards energy companies and government entities, perceptions of unfair decision-making processes, and feelings of powerlessness over energy decisions (Bradbury et al., 2009). L'Orange Seigo et al. (2014) further illuminate this complex landscape, noting that acceptance can differ between broader societal levels and specific local projects. They characterize the general public's attitude as "reluctant acceptance," where people do not completely reject CCUS, but instead view it as an imperfect solution (L'Orange Seigo et al., 2014). This nuanced perspective underscores the complexity of public opinion on CCUS and the importance of addressing both technical and social aspects in project implementation.

Environmental justice (EJ) concerns play a critical role in the development and implementation of CCUS projects. These concerns often become the primary focus of opposition from EJ communities, stemming from the uneven distribution of risks and benefits associated with such initiatives. Research has shown that rural communities, in particular, have expressed apprehension about CCUS projects. Their main worry is that these projects may concentrate risks in certain areas while distributing benefits and risks unevenly (Witt et al., 2020; Shaw et al., 2015). This imbalance can exacerbate existing environmental and social inequalities. The implementation of CCUS projects in vulnerable communities without adequate safeguards could potentially worsen environmental injustices and health disparities (Rajas-Rueda et al., 2024). Therefore, addressing these EJ concerns is not just a matter of project acceptance, but a crucial step in ensuring that CCUS implementation aligns with the broader policy goal of achieving "just transitions" in the move toward a low-carbon future (Swennenhuis et al., 2020). Policymakers should develop strategies, such as compensation schemes, to mitigate negative impacts while promoting CCUS projects to enhance climate justice in local communities. As energy hubs become more prevalent, public and private sectors should collaborate to enhance community engagement and understanding of CCUS projects. This involves facilitating open discussions about the potential benefits, costs, and risks associated with CCUS initiatives. By promoting transparent communication and active public participation, stakeholders can work towards informed decision-making and more sustainable project outcomes, rather than simply aiming to minimize objections.

There are several directions for future studies. First, the relevance of our findings may differ across regulatory landscapes. For instance, in the European Union, there are regulatory requirements and economic considerations for CCUS and EOR, potentially constraining their implementation compared to other regions (European Parliament and Council of the European Union, 2009). While our study shows increased property values near CCUS operations in the U.S., these results should be carefully interpreted when considering CCUS development in other countries. Local regulatory frameworks, economic conditions, and social factors play crucial roles in determining the impact of CCUS projects and must be thoroughly evaluated in each unique context.

Second, there are certain limitations inherent to the ZTRAX dataset. While the ZTRAX dataset offers comprehensive information on housing transactions, including officially recorded final selling prices, it’s important to recognize its potential limitations. The dataset may not capture private agreements between buyers and sellers that occur outside the official record. These could include additional payments, contingencies, or other arrangements that might affect the property’s effective price but are not reflected in the recorded sale price. However, these additional terms that involve monetary transfers are mostly a tiny fraction of the final selling prices. Such limitations are common to most large-scale housing transaction datasets and are not unique to our study. Although we believe our findings offer valuable insights into the relationship between CCUS projects and housing prices, future research could benefit from supplementing transaction data with surveys or interviews. This approach could help capture off-record agreements that might influence property valuation, providing a more comprehensive understanding of the market dynamics.

Third, we acknowledge that public knowledge about CCUS is often limited, and local communities may not be fully aware of CCUS installations and their implications. Our study assumes that the presence of CCUS projects influences housing prices, potentially through direct awareness of the technology or indirect effects such as increased economic activity or infrastructure improvements. Future research could benefit from incorporating measures of public awareness and knowledge about CCUS to better understand the mechanisms behind these price effects. Despite potential limitations in public understanding, our results suggest that CCUS projects have a measurable impact on nearby property values, contrasting with the negative effects often seen with renewable energy projects like wind and solar (Dröes & Koster, 2016; Gibbons, 2015).

Fourth, it is important to note that our study focuses exclusively on industrial CCUS projects, as our sample does not include any Direct Air Capture (DAC) installations. DAC technology has attracted interest for its potential use in various settings, including residential areas, due to its smaller physical footprint compared to other carbon removal methods (Beuttler et al., 2019). However, our data do not allow us to conclude its specific impacts. Future research could explore potential differences in community responses to industrial CCUS versus DAC projects in residential contexts.

Lastly, while CCUS projects contribute to global efforts to reduce carbon emissions, our estimation strategy captures only localized effects on property values. The global benefits of reduced carbon emissions and potential long-term climate impacts are not reflected in these local price premiums.

Methods

Data

The Global CCS Institute (2024) 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, and synthetic natural gas), and facility location. As of June 2024, there are 28 operational CCUS projects in the U.S., with an additional 8 under construction (Global CCS Institute, 2024).

Our study includes 25 CCUS projects not located in remote areas (i.e., with residential communities within 10 miles). **Fig. 3** illustrates the locations of CCUS sites in the United States which are typically located in oil and gas fields or basins. The operational years of the 25 CCUS projects range from 2000 to 2018. Carbon capture projects include carbon capture facilities, carbon capture tests, and carbon capture technology tests. Supplementary Note 1 investigates the carbon capture technologies used in our study, highlighting key differences between capturing CO2 from industrial processes or flue gases and direct air capture (DAC). Carbon storage projects include carbon storage facilities, enhanced oil recovery (EOR) projects, storage performance tests, and CO_2 injection and monitor projects. 16 of the CCUS projects are carbon capture projects, 12 are carbon storage projects, and 3 are carbon capture and storage projects (site 17, site 26, and site 31 in Supplementary Tables 1 and 2[7]). As for facility conditions, 19 are newly built projects, while 6 are retrofitted projects. Retrofitted projects include (1) projects

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[7] See Supplementary Tables 1 and 2 for detail information of each site. The site id here is labelled by the authors for ease of exposition. The following CCUS sites are included in main sample for having house transactions within 30 km: site1, site2, site4, site5, site8 - site11, site13 - site17, site21 - site24, site26 - site28, site30 - site33, and site37.

retrofitting a CO_2 capture/storage facility (site1, site16, and site26[8]) 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).

Zillow provides individual housing transaction data through the Zillow Transaction and Assessment Dataset (ZTRAX)[9]. The dataset provides historical transaction and assessment records (including sale prices, locations, and transaction dates) with property-level building attributes such as the number of rooms, building area, and year built. Based on the latitude and longitude of each house transaction, we assign the closest CCUS site to individual properties. Our main estimation includes only arm's length transactions. We also exclude houses from our sample that were remodeled after 2000 (about 1.9% of the total sample) to eliminate any influence of remodeling on the estimation of a price premium. Not every arm's length transaction in the U.S. is included in our sample as houses located too far away from a CCUS site do not contribute to our analysis. Our sample includes only houses within 30 km of a CCUS project and there are 555,938 transactions of properties located within 30 km of a CCUS project from 1990 to 2021.[10] Supplementary Note 2 provides a detailed description of the data preprocessing steps.

Housing prices are converted into 2021 dollars adjusted for inflation. In Supplementary Table 5, 16 states have houses within 30 km of a CCUS site. Our sample contains more than 240,000 house transactions in Illinois. Kansas has the lowest average property price, $80,894, while Colorado has the highest at $278,038 in our sample. Supplementary Table 6 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 and a cross-sectional sample after matching. Column 3 of Supplementary Table 6 presents *t*-test results that compare the building characteristics of the full and cross-sectional samples. Houses in the treatment group are within the impact buffer, 4.2 km of CCUS projects, whereas houses in the control group are outside the buffer (but still within 30 km[11] of the nearest CCUS project). The term buffer refers to the distance beyond which CCUS projects do not affect the housing

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[8] Information of retrofitted CCUS projects in the U.S. are from ZEROCO2.NO (http://www.zeroco2.no/projects/countries/usa).

[9] Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author(s) and do not reflect the position of Zillow Group. We are restricted by a non-disclosure agreement and cannot share the Zillow data publicly. The program has ended and will no longer be updated. The conclusions drawn in this study based on this data were completed before the access policy change.

[10] 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.

[11] Despite not expecting the impact of CCUS to reach a radius of 30 km, we choose 30 km to include enough properties for the control group. Choosing 30 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 50 km. The robustness check illustrates that our main results are not sensitive to the outer boundary we chose.

market in the surrounding area. Detailed information regarding buffer estimation is provided in the Buffer section. Comparing the treated group with the control group, we find that the treated buildings are slightly older, smaller (in terms of building area), more expensive (in terms of land value), and have fewer rooms and stories than the control houses on average.

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 the U.S. Energy Information Administration (EIA)[12]. Data on population density and personal income per capita (1969-2020) are retrieved from the Bureau of Economic Analysis, U.S. Department of Commerce[13]. Data on annual electricity prices (1990-2020) [14] and monthly natural gas prices (1989-2021)[15] 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[16]. Data on PM 2.5 concentration (2001-2020) are derived from the Centers for Disease Control and Prevention[17]. The number of business establishments at the zip-code level (1994-2020) is obtained from the U.S. Census Bureau[18].

Empirical strategy

As shown in **Fig. 3**, 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 & Shackley, 2006). Therefore, self-selection based on location may be possible. Furthermore, concurrent changes may occur 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 property 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 proximity to the CCUS, which avoids arbitrarily defining the treatment distance as inappropriate buffer selection could introduce bias into the study. Third, we employ an event

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[12] EIA. Maps: Oil and Gas Exploration, Resources, and Production. U.S. and lower 48 states. Map data. https://www.eia.gov/maps/maps.htm.

[13] Bureau of Economic Analysis, US Department of Commerce. Regional data: GDP and income. https://apps.bea.gov/iTable/index_regional.cfm.

[14] EIA. Detailed State Data. https://www.eia.gov/electricity/data/state/.

[15] EIA. Natural gas prices. https://www.eia.gov/dnav/ng/ng_pri_sum_a_EPG0_PRS_DMcf_m.htm.

[16] Yale Program on Climate Change Communication. https://climatecommunication.yale.edu/visualizations-data/#visualizations-data-search-filter.

[17] Centers for Disease Control and Prevention. Daily County-Level PM2.5 Concentrations, 2001-2019. https://data.cdc.gov/browse/select_dataset?tags=pm2.5.

[18] County Business Patterns (CBP) Datasets, US census bureau. https://www.census.gov/programs-surveys/cbp/data/datasets.html.

study analysis in a difference-in-differences framework to demonstrate that price trends are comparable before the treatment, to demonstrate that the estimated positive effects are unlikely 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. Lastly, we also consider heterogeneous responses resulting from varying environmental attitudes among household owners and the industry in which the nearest CCUS project operates. The following sections provide a detailed description of our empirical strategies.

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 following three steps. We first select a subset of properties sold more than once and have at least one transaction made after operating only one CCUS facility within 30 km.[19] We then 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, total rooms, total bedrooms, and building area (in square footage). The CCUS fixed effects, and the property fixed effects are perfectly collinear, therefore we drop the CCUS fixed effects. Lastly, we estimate two price functions based on the distance to the nearest CCUS site, including the price function for properties sold before the CCUS operation and one for properties sold after. We estimate price functions using local polynomial regressions with the estimated residuals as the dependent variables.

DID estimation

The overall net effect of the CCUS operation is estimated with the difference-in-differences (DID) methodology. We exclude houses from our sample that were remodeled after 2000 to avoid the impact of remodeling on housing prices. Differences in the levels of building attributes are controlled in the empirical model. The DID model is specified as follows:

$$lnY_{ict} = \beta_{1,b} \sum_{b}^{B} Vicinity_{itb} \times Post_{itb} + \beta_2 Post_{it} + \beta_3 BA_{it} + \boldsymbol{X}'_{\boldsymbol{ct}}\boldsymbol{\varphi} + \sigma_c \times \vartheta_y + \gamma_i + \omega_y + \mu_m + \varepsilon_{ict} \tag{1}$$

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[19] We choose to only look at houses that have only *one* CCUS facility within 30 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 30 km to include enough properties for constructing the control group even though we do not expect the impact of CCUS to reach a 30-km radius. The 30-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 10 km to 50 km. We find that our main results are not sensitive to the outer boundary we selected.

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. $Vicinity_{itb}$ takes a value of one only if house *i* is in the distance bin b, and zero otherwise. $Post_{it}$ takes the values of one if house i is sold after the operational year of the nearest CCUS project[20], and zero otherwise. 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. $\boldsymbol{X}'_{\boldsymbol{ct}}$ is a vector of covariates such as personal income per capita, population density, and PM2.5 concentration at the county level, and the number of business establishments at the zip code level. γ_i controls property fixed effects. $\sigma_c \times \vartheta_y$ represents county-by-year fixed effects, ω_y represents the year fixed effects, and μ_m represents month-of-sample fixed effects. Year fixed effects and county-by-year fixed effects are not included simultaneously in the same equation. In our sample, one house is assigned to the closest CCUS project, which leads to collinearity between property fixed effects and CCUS fixed effects. The CCUS fixed effects are effectively controlled with the inclusion of property fixed effects. BA_{it} is the building age of house *i* at day *t*. ε_{ict} is an idiosyncratic error term. The main model clusters the standard errors at the individual house, allowing for correlations between observations within the same house. We use 4 distance bins, ranging from 0 km to 4.2 km, with a 1-km increment, to explore how the effects differ as the distance increases.

Coarsened exact matching with DID

While our primary Difference-in-Differences (DID) approach relies on intertemporal price variation, it may be susceptible to bias from shifts in the hedonic gradient over time (Kuminoff & Pope, 2014). To address this potential issue and enhance the robustness of our findings, we employ a combined approach of Coarsened Exact Matching (CEM) and DID.

We opt for CEM over other matching methods, such as Propensity Score Matching (PSM), following recent criticisms that PSM can increase imbalance, inefficiency, model dependence, and bias, particularly after approximating complete randomization, making it suboptimal compared to methods that better approximate fully blocked experiments (King & Nielsen, 2019). CEM offers the advantage of retaining more treatment observations while better approximating fully blocked experiments (Iacus et al., 2012). However, the matching covariates in our dataset may not contain all the important house features. Thus, while this cross-sectional estimation with matching serves as a valuable robustness check, we still prefer the DID specification for our main analysis as it better controls time-invariant, unobserved variables.

Our matching process begins with an exact match in the time dimension (transaction year) to account for unobserved time-variant factors, and in the geographic dimension (county) to control for unobservable neighborhood characteristics. We then apply CEM to identify one control transaction for each treated transaction based on time-invariant building features (Qiu et al.,

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[20] 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.

2017). The matching covariates include key house characteristics such as building age, number of rooms, number of bedrooms, number of stories, and building area.

Using this matched sample, we perform the same DID framework as in our main analysis, maintaining the same distance bin settings, fixed effects, and covariates. This approach combines the strengths of matching methods in controlling for observable characteristics with the DID method's ability to account for time-invariant unobserved variables.

Heterogeneity analyses

Individuals may respond differently depending on factors such as their environmental awareness and the industry in which the closest CCUS project operates. To examine the heterogeneity of the price impact, a flexible semiparametric approach is employed using the partially linear varying coefficient fixed effects panel data following Shen et al. (2021). The model is specified as follows:

$$lnY_{iy} = D_{iy} \times g(U_{iy}) + \boldsymbol{X'_{iy}\theta} + \rho_j + \vartheta_y + \varepsilon_{iy} \tag{2}$$

where lnY_{iy} is the natural logarithm of the sales price of house i in year y. Housing prices are converted into 2021 dollars adjusted for inflation rates. We collapse the data at the household by year level to perform the empirical analysis. D_{iy} is the post-treatment variable with a functional-coefficient $g(U_{iy})$ and U_{iy} is a continuous variable to be examined for heterogeneity, including environmental awareness (measured by the percentage of residents who believe global warming is happening) at the county level and industry of the CCUS projects. $\boldsymbol{X'_{iy}}$ is a vector of covariates such as federal fund rates, demographic features by county level, and the prices 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.

We employ a semiparametric panel data method (Li & Racine, 2010) involving a two-step procedure. First, we estimate linear coefficients $\boldsymbol{\theta}$ and fixed effects ρ_j and ϑ_y. Second, we use a local linear regression approach to estimate the functional coefficient $g(U_{iy})$, allowing for flexible estimation of the non-linear relationship between environmental awareness and the price impact of CCUS projects.

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, 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 before the CCUS operation and five waves after it and exclude the period right before the CCUS operation (where m = 1). However, effects from other periods may contaminate the coefficient for a given lead or lag. To adjust bias, we employ an alternative estimator free of contamination following Sun and Abraham (2021).[21] Below is the specification of the event study model:

$$lnY_{it} = \alpha BE_{zy} + \boldsymbol{X'}_{\boldsymbol{it}}\boldsymbol{\beta} + \sum_{m=2}^{M} \rho_m (Lag\ m)_{it} + \sum_{n=1}^{N} \delta_n (Lead\ n)_{it} + \gamma_i + \sigma_c \times \vartheta_y + \varepsilon_{it} \quad (3)$$

where 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. $\boldsymbol{X'}_{\boldsymbol{it}}$ 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. Other variables and fixed effects follow the same definitions as in equation (1). ε_{iy} is an idiosyncratic error term. We cluster our standard errors at the household level.

Data availability

House transaction and building feature data was derived from the Zillow Transaction and Assessment Database (ZTRAX). We are bound by a non-disclosure agreement and are unable to share the data publicly. There will be no further updates to this program because it has been discontinued. These conclusions are based on data collected before the change in access policy was implemented. Other data used in this study were derived from publicly accessible sources. The sources for each covariate are outlined in the Methods - Data section. All other data, except Zillow data, is available on GitHub at https://github.com/kluo2019/CCUS.

Code availability

Data preprocessing and analysis were performed in Stata SE (16.0). The custom code is available on GitHub at https://github.com/kluo2019/CCUS.

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

Author contributions

K.L., Y.Q., and P.L. conceived and designed the paper, and planned the analysis. K.L. conducted the analysis, drafted the paper, and revised it. Y.Q., P.L., and Y.M. offered revision comments and edited the paper.

Competing interests

The authors declare no competing interests.

Inclusion and ethics statement

We pledge to promote an inclusive culture. We commit to cultivating an environment and culture that welcomes and values participation by all individuals who contribute to the mission.

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