Supplementary Information for

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

Kaifang Luo [a, b], Yueming (Lucy) Qiu [c, *], Pengfei Liu [d], Yingdan Mei [e]

[a] Marxe School of Public and International Affairs, Baruch College, City University of New York

[b] CUNY Institute for Demographic Research, City University of New York

[c] School of Public Policy, University of Maryland at College Park

[d] Department of Environmental and Natural Resource Economics, University of Rhode Island

[e] School of Applied Economics, Renmin University of China

[*] Corresponding author: yqiu16@umd.edu

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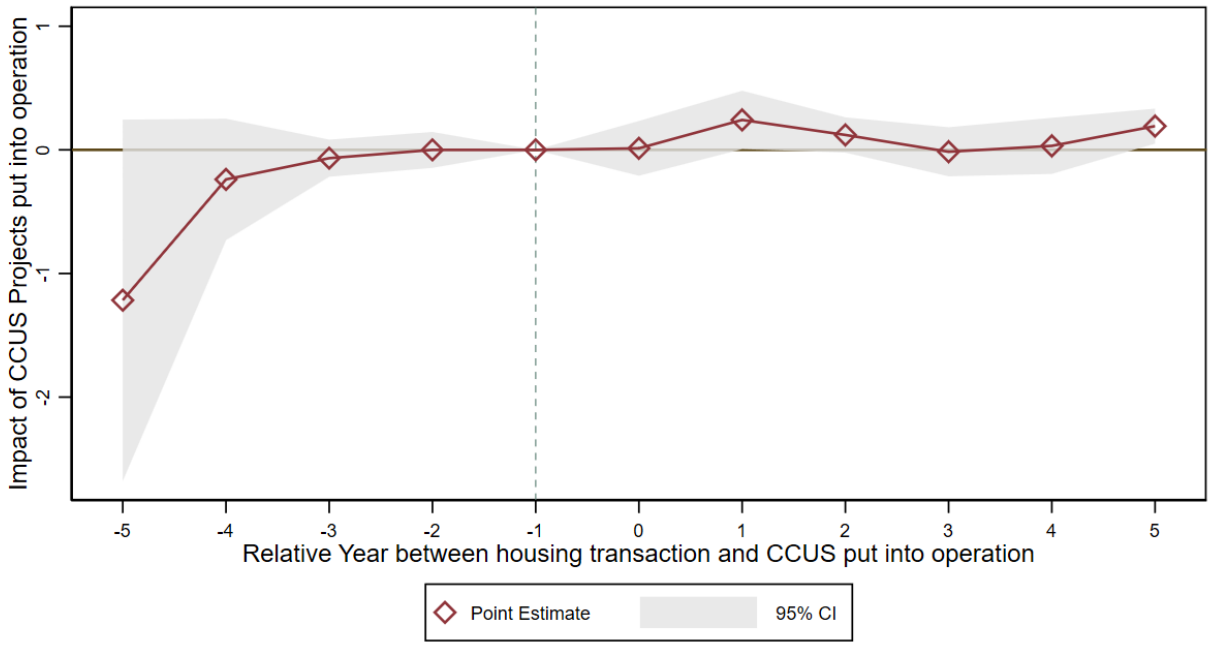
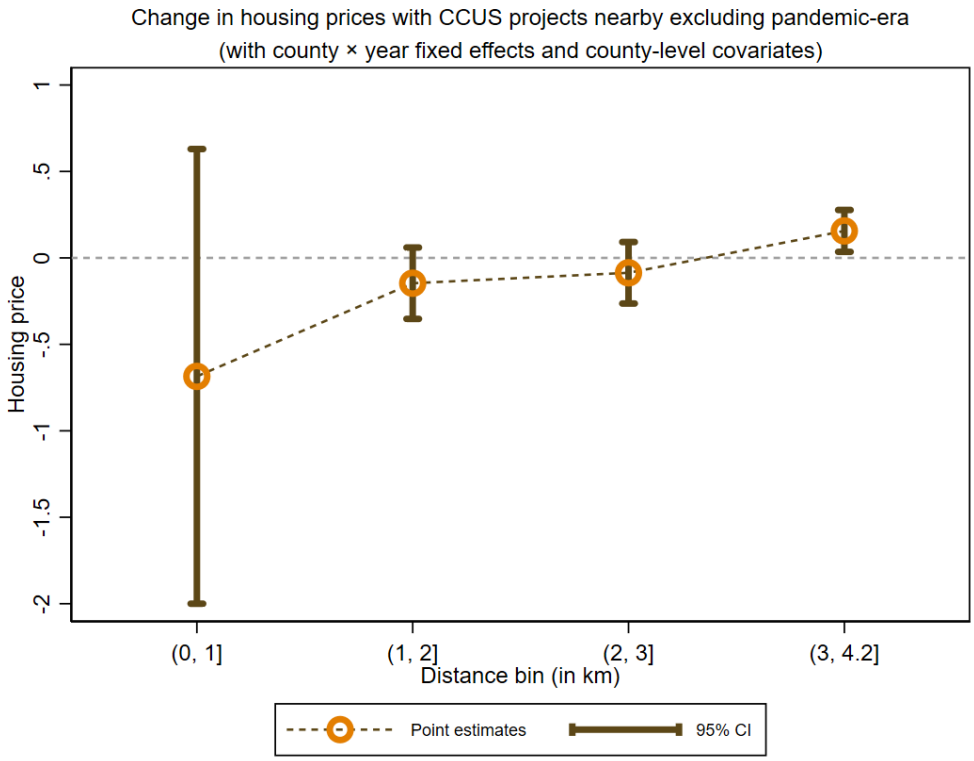
Supplementary information

Supplementary Figure 1. A screenshot of the website called "Citizens against CO2 sequestration".



Supplementary Figure 2. Event study evidence for DID approach. The first lag m=1 is the excluded period. We have dropped the observations before lag m = 5 and following lead n = 5. The standard errors are clustered by household. We include household and county-by-year fixed effects. The number of treated households is 2,456, and the number of control households is 139,697.



Supplementary Figure 3. Adjacency impacts of CCUS projects excluding pandemic influence. 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. 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 cluster at the household level. There are 517,180 observations left for analysis when excluding COVID transactions.

Supplementary Table 1. 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 names for CCUS projects in the United States are provided by Global CCS Institute (https://co2re.co/FacilityData).

Supplementary Table 2. Information on 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

Note: 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 the 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.

Supplementary Table 3. Cross-sectional results using matched samples.

	Outcome: Natural log of home prices (2021$)	
	Main results	Matching with DID results
Average housing price premium	3.90%	3.24%
Vicinity 0 – 1 km	-0.6851	-0.6678
	(0.6708)	(0.5983)
Vicinity 1 – 2 km	-0.1464	-0.0866
	(0.1053)	(0.1049)
Vicinity 2 – 3 km	-0.0861	-0.0767
	(0.0908)	(0.0945)
Vicinity 3 – 4.2 km	0.1560*	0.1296*
	(0.0618)	(0.0613)
Observations	264,318	34,153
R-sq	0.243	0.162
Building age control	Yes	Yes
County-level covariates	Yes	Yes
Property FE	Yes	Yes
Month-by-sample FE	Yes	Yes
County-by-year FE	Yes	Yes

Note: The dependent variable is log housing 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 "Average housing price premium" is calculated by averaging the non-omitted coefficients for housing price change across all properties within 4 distance bins.

Supplementary Table 4. DID robustness check: changing the outer boundary of the control group.

	Outcome: Natural log of home prices (2021$)				
Model	**1**	**2**	**3**	**4**	**5**
The outer boundary of the control group	10 km	20 km	30 km	40 km	50 km
Average housing price premium	5.07%	4.39%	4.14%	4.02%	3.98%
Vicinity 0.8-1 km	-0.1902	-0.1833	-0.0977	-0.0580	-0.0559
	(0.3626)	(0.3723)	(0.3888)	(0.3822)	(0.3830)
Vicinity 1-1.2 km	0.2406	0.1175	0.1335	0.1532	0.1542
	(0.2588)	(0.2379)	(0.2351)	(0.2311)	(0.2337)
Vicinity 1.2-1.4 km	0.0884	0.0317	0.0456	0.0481	0.0455
	(0.1782)	(0.1798)	(0.1766)	(0.1765)	(0.1765)
Vicinity 1.4-1.6 km	-0.0916	-0.1083	-0.1317	-0.1194	-0.1245
	(0.1381)	(0.1342)	(0.1319)	(0.1289)	(0.1290)
Vicinity 1.6-1.8 km	-0.0227	-0.0725	-0.0678	-0.0668	-0.0726
	(0.1292)	(0.1287)	(0.1297)	(0.1302)	(0.1307)
Vicinity 1.8-2 km	0.0157	-0.0371	-0.0442	-0.0505	-0.0510
	(0.0636)	(0.0613)	(0.0618)	(0.0609)	(0.0611)
Vicinity 2-2.2 km	-0.0288	-0.0448	-0.0776	-0.0686	-0.0699
	(0.0944)	(0.0952)	(0.0954)	(0.0957)	(0.0955)
Vicinity 2.2-2.4 km	0.0372	-0.0665	-0.0727	-0.0706	-0.0670
	(0.1697)	(0.1628)	(0.1668)	(0.1663)	(0.1661)
Vicinity 2.4-2.6 km	-0.2543	-0.3111	-0.3366	-0.3324	-0.3351
	(0.2399)	(0.2381)	(0.2405)	(0.2411)	(0.2406)
Vicinity 2.6-2.8 km	0.0145	-0.0230	-0.0321	-0.0255	-0.0222
	(0.1206)	(0.1177)	(0.1197)	(0.1192)	(0.1192)
Vicinity 2.8-3 km	0.0705	0.0253	0.0181	0.0131	0.0105
	(0.0734)	(0.0750)	(0.0749)	(0.0750)	(0.0754)
Vicinity 3-3.2 km	0.2929***	0.2667***	0.2418**	0.2334**	0.2323**
	(0.0788)	(0.0789)	(0.0784)	(0.0786)	(0.0783)
Vicinity 3.2-3.4 km	0.2866**	0.2401**	0.2278*	0.2208*	0.2177*
	(0.0923)	(0.0918)	(0.0913)	(0.0920)	(0.0918)
Vicinity 3.4-3.6 km	-0.0472	-0.0878	-0.0999	-0.1023	-0.1007
	(0.1109)	(0.1131)	(0.1127)	(0.1129)	(0.1128)
Vicinity 3.6-3.8 km	0.2829***	0.2397***	0.2335***	0.2291***	0.2272***
	(0.0672)	(0.0662)	(0.0659)	(0.0656)	(0.0657)
Vicinity 3.8-4 km	0.0611	0.0164	0.0177	0.0134	0.0110
	(0.0764)	(0.0753)	(0.0756)	(0.0755)	(0.0756)
Vicinity 4-4.2 km	0.0857	0.0646	0.0624	0.0631	0.0631
	(0.0504)	(0.0497)	(0.0511)	(0.0514)	(0.0515)
Observations	38255	132240	318742	318742	318742
R-sq	0.171	0.192	0.167	0.167	0.167
Building age control	Yes	Yes	Yes	Yes	Yes
Demographic control	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Month-of-sample FE	Yes	Yes	Yes	Yes	Yes
County-by-year FE	Yes	Yes	Yes	Yes	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 "Average housing price premium" is calculated by averaging the non-omitted coefficients for housing price change across all properties within 4 distance bins.

Supplementary Table 5. The distribution of transactions and descriptive statistics of housing prices.

States	No. of Transactions	Average House Price ($ in 2021)	Std. Dev. of House Price
AL	67,560	248,472	260,598
CO	137	278,038	206,559
IL	243,448	262,708	279,788
IN	542	138,697	215,386
KS	406	80,894	83,911
KY	82,066	201,150	252,042
MI	11,647	129,233	140,303
MS	99	97,280	148,653
ND	801	142,239	137,587
NM	232	126,270	95,891
OK	320	91,250	117,159
PA	478	108,267	125,615
TX	80,289	122,589	200,251
WI	59,662	208,774	302,799
WV	7,093	95,699	141,202
WY	1,158	195,299	103,695
Total	555,938	220,058	266,661

Note: The ZTRAX dataset provides information regarding each transaction. There can be several transactions associated with one house. In this table, descriptive statistics are presented at the transaction level, not at the house level.

Supplementary Table 6. Comparison of the full sample and cross-sectional matched sample concerning building characteristics between treatment and control houses.

	Full sample	Cross-sectional sample	*p*-value (1) versus (2)
	(1)	(2)	(3)
No. of Treated Transactions	**10,705**	**7,253**	
Year built	1975.65	1976.71	0.0072
No of stories	1.25	1.25	0.5599
Total rooms	4.04	3.6	0.0003
Total bedrooms	2.88	2.83	0.0227
Building area (Sq Ft)	1608.70	1557.19	0.0000
Land value ($)	42579.84	29819.65	0.0000
No. of Control Transactions	**545,233**	**42,180**	
Year built	1980.05	1976.07	0.0000
No of stories	1.42	1.15	0.0000
Total rooms	4.63	3.74	0.0000
Total bedrooms	2.92	2.73	0.0000
Building area (Sq Ft)	2074.94	1565.92	0.0000
Land value ($)	25814.86	23529.38	0.0000

Note: Control transactions are those involving houses located between 4.2 km and 30 km from CCUS projects, while treated transactions are those involving houses within 4.2 km based on an estimation of the buffer distance later.

Supplementary Note 1: Carbon Capture Technologies in the Sample

This note investigates the carbon capture technologies used in our study, highlighting key differences between capturing CO_2 from industrial processes or flue gases and direct air capture (DAC). The choice of technology can significantly affect factors such as efficiency and scalability.

In terms of efficiency, capturing CO_2 from industrial sources is more efficient than DAC due to higher CO2 concentrations in flue gases. Power plant flue gases contain approximately 4-14% CO_2, compared to only 0.04% in ambient air. This difference means that capturing CO_2 from industrial sources requires less energy than capturing an equivalent amount using DAC technology (Wilcox et al., 2017).

In terms of scalability, capturing CO_2 from industrial processes can be more readily integrated into existing infrastructure, making it more feasible in the near term (Bui et al., 2018). While DAC technology shows promise for removing CO_2 from the atmosphere, it is still in the early stages of development and deployment, with few large-scale projects currently in operation (Beuttler et al., 2019).

According to the short descriptions provided by the Global CCS Institute (https://co2re.co/FacilityData), our sample of 16 carbon capture projects primarily involves capturing CO_2 from industrial sources, such as ethanol production, natural gas treatment, coal gasification, and power plants. None of the projects in our sample use DAC technology. Below is a breakdown of carbon capture projects in our sample:

1. Air Products Steam Methane Reformer: Captures CO_2 from the process gas stream of steam methane reformers.

2. Arkalon CO2 Compression Facility: Captures CO_2 from an ethanol plant.

3. Bonanza BioEnergy CCUS EOR: Captures CO_2 from an ethanol plant.

4. Borger CO2 Compression Facility: Captured CO_2 from a fertilizer plant (no longer operating).

5. Coffeyville Gasification Plant: Captures CO_2 from a fertilizer plant.

6. E.W. Brown 0.7 MWe Pilot Carbon Capture Unit: Captures CO_2 from a coal-fired power plant.

7. Fuel Cell Carbon Capture Pilot Plant: Captures CO_2 from the exhaust flue gases of a natural gas-fired power plant.

8. Great Plains Synfuels Plant and Weyburn-Midale: Captures CO_2 from a coal gasification process.

9. Illinois Basin Decatur Project: Captured CO_2 from a corn-to-ethanol plant.

10. Mountaineer Validation Facility: Captured CO_2 from a coal-fired power plant.

11. National Carbon Capture Center (NCCC): Tests carbon capture technologies using coal-derived flue gas and syngas.

12. NET Power Clean Energy Large-scale Pilot Plant: Uses CO_2 as a working fluid in a natural gas-fired power plant (Allam Cycle).

13. Petra Nova Carbon Capture: Captured CO_2 from a coal-fired power plant.

14. Plant Barry & Citronelle Integrated Project: Captured CO_2 from a coal-fired power plant.

15. Pleasant Prairie Power Plant Field Pilot: Tested CO_2 post-combustion capture technology at a coal-fired power plant.

16. Wyoming Integrated Test Center (ITC): Provides carbon capture tests using coal-based flue gas.

It is important to note that our analysis does not include CCUS projects that were operated before 2000 or located in remote locations (i.e., no community within 10 miles). Some of these excluded projects may utilize DAC technology.

As our sample focuses on industrial processes and flue gas capture, our analysis does not include the potential differential impacts of DAC technology. We believe our estimation remains reliable and representative of the industrial processes capturing technologies. Future research could explore the economic and environmental consequences of DAC projects as they become more widespread.

Supplementary Note 2: Data Preprocessing of ZTRAX Dataset

The Zillow Transaction and Assessment Dataset (ZTRAX) offers comprehensive information on real estate transactions and property characteristics across the United States. However, like any large-scale dataset, the Zillow dataset presents challenges related to accuracy and missing data (Nolte et al., 2024). To address these issues and ensure a robust analysis, we implement a thorough data preprocessing procedure.

Our data-cleaning process begins with the removal of duplicate observations and outliers. We exclude properties with prices falling outside two standard deviations of the state average to eliminate unusual transactions. For consistency, we also remove instances of multiple same-day transactions at different prices for the same property.

Given our focus on housing prices, we exclude transactions involving only land sales without residential structures. This step ensures our analysis remains relevant to the housing market specifically.

To address concerns about the accuracy of geographic coordinates, particularly in less populated areas, we employed a two-pronged approach. First, we validate the accuracy of 100 randomly selected locations by cross-referencing ZTRAX coordinates with U.S. Census Bureau data and using a Stata command called Opencagegeo[1], a geocoding API service. Second, we conduct a sensitivity analysis by repeating our main model while excluding transactions in low-density areas, defined as those below the 10th percentile of population density. The results, detailed in **Supplementary Table 7**, demonstrate that our main conclusions remain stable, indicating that our results are robust to potential location inaccuracies in low-density areas.

Supplementary Table 7. Estimate CCUS impacts excluding transactions in low-density areas.

	Outcome: Natural log of home prices (2021$)	
	Main results	Results excluding low-density areas
Average housing price premium	3.90%	3.74%
Vicinity 0 – 1 km	-0.6851	-0.8369
	(0.6708)	(0.7758)
Vicinity 1 – 2 km	-0.1464	-0.1423
	(0.1053)	(0.1110)
Vicinity 2 – 3 km	-0.0861	-0.0585
	(0.0908)	(0.0929)
Vicinity 3 – 4.2 km	0.1560*	0.1497*
	(0.0618)	(0.0632)
Observations	264,318	246,798
R-sq	0.243	0.252
Building age control	Yes	Yes
County-level covariates	Yes	Yes
Property FE	Yes	Yes
Month-by-sample FE	Yes	Yes
County-by-year FE	Yes	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 "Average housing price premium" is calculated by averaging the non-omitted coefficients for housing price change across all properties within 4 distance bins.

Lastly, to focus on market-driven transactions, we filter the data to include only arm's length deals. We retain only deed transfers with non-zero sale amounts and exclude intra-family transfers by filtering the

[1] Stata Geocoding Tutorial: https://opencagedata.com/tutorials/geocode-in-stata.

data based on the "*dataclassstndcode* (data class code)", "*intrafamilytransferflag* (intra-family transfer)", and "*salespriceamount* (sale amount)" fields in ZTRAX[2]. Specifically, we keep only deed transfers (e.g., "D" for deed transfer and "H" for deed with a concurrent mortgage), non-intrafamily transfers (not coded as "Y"), and transactions with a non-zero sale amount. Additionally, we remove properties sold multiple times within a year to minimize the influence of speculative behavior or unusual transaction patterns.

These comprehensive preprocessing steps, informed by the recommendations of Nolte et al. (2024), address potential data quality issues, enhancing the reliability and validity of our subsequent analysis. By carefully curating the ZTRAX dataset, we establish a solid foundation for studying the impacts of environmental factors on housing prices.

[2] ZTRAX data dictionary: http://files.zillowstatic.com/research/public/StaticFiles/ZTRAX/ZTRAXDataDictionary.zip.

Supplementary Note 3: Repeat Sales Sample with 0.2 km Distance Bins

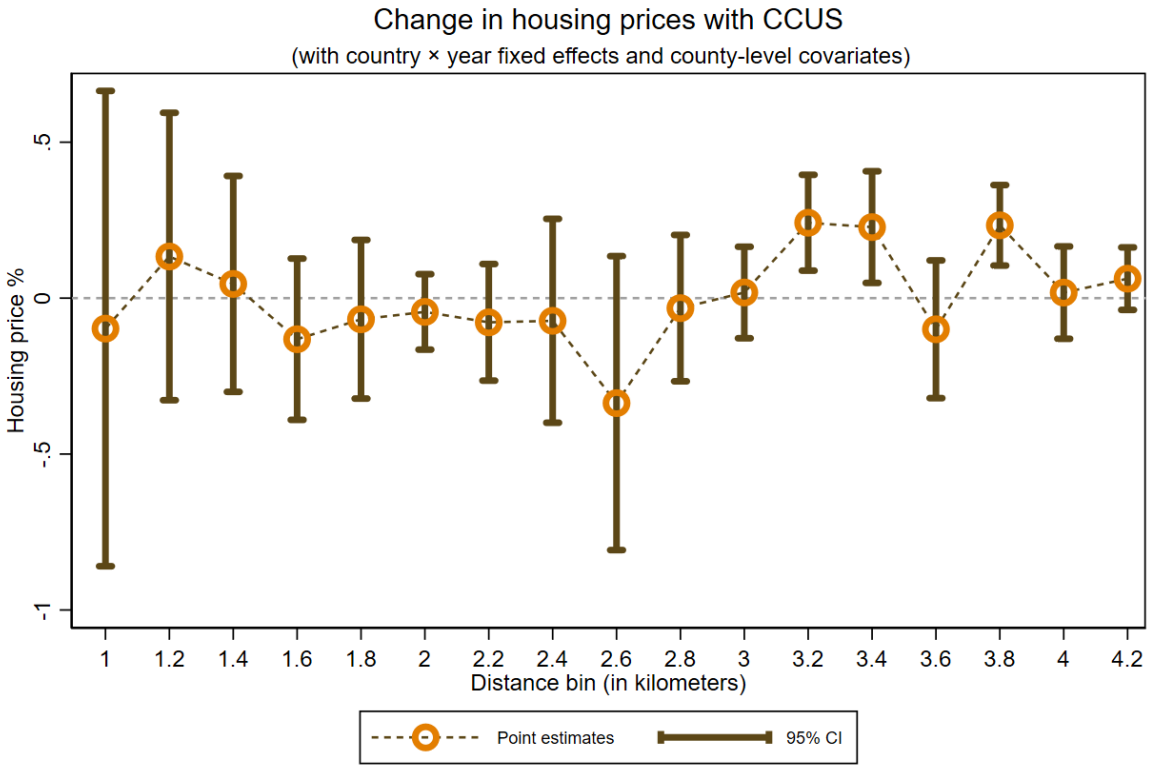
To further assess the robustness of our findings, we conduct an additional analysis using the repeat sales sample and finer distance bins of 0.2 km. While our main analysis focuses on the full sample with 1 km distance bins to enhance statistical power and representativeness, it is important to examine whether the results hold when using the repeat sales sample and more granular distance measures.

For this robustness check, we estimate the same model specification as in our main analysis, but with the following changes:

1. Sample: We use the repeat sales sample, which includes only properties that have been sold at least twice during the study period – once before and once after CCUS operation. This allows us to control for unobserved property characteristics that may influence housing prices.
2. Distance bins: We use 0.2 km distance bins to measure the proximity of properties to CCUS projects. This finer granularity allows us to examine the spatial pattern of the CCUS effect on housing prices in more detail. Nevertheless, the results may be noisy compared with our main results since fewer transactions occurred in smaller distance bins.

The robustness check yields an average housing price premium of 4.14% (see **Supplementary Figure 4** and **Supplementary Table 8** column 3), which is consistent with our main findings (3.90%). The spatial pattern of the CCUS effect is also similar, with significant positive impacts observed in the vicinity of 3 to 3.8 km from the project site.

It is worth noting that the repeat sales sample may suffer from selection bias and sparseness issues, particularly in low-density areas where CCUS projects are typically located. The consistency of the results between the main analysis and the robustness check, despite these limitations, strengthens the validity of our conclusions.



Supplementary Figure 4. Impacts of proximity to CCUS projects on housing prices using repeat sales sample. 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 3 of **Supplementary Table 8**). The dependent variable is the natural log of house sales prices in 2021 dollars. The label of a tick represents the upper limit of a distance bin. For example, 1 means the distance bin of (0.8, 1] km. 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 cluster at the household level. There are 271,680 observations in total for the regression analysis. There are 3,297 house transactions close to CCUS projects within 4.2 km and 268,383 transactions without proximity to CCUS projects.

Supplementary Table 8. The estimation of CCUS impacts using the repeat sales sample.

	Outcome: Natural log of home prices (2021$)		
	1	2	3
	Year fixed effects	County-by-year fixed effects	County-by-year fixed effects + county-level covariates
Average housing price premium	8.51%	4.91%	4.14%
Vicinity 0.6-0.8 km	0.3517***	0.1389**	N/A
	(0.0109)	(0.0505)	N/A
Vicinity 0.8-1 km	0.1664	-0.0962	-0.0977
	(0.3776)	(0.3805)	(0.3888)
Vicinity 1-1.2 km	0.2243	0.1647	0.1335
	(0.2558)	(0.2467)	(0.2351)
Vicinity 1.2-1.4 km	0.1310	0.0888	0.0456
	(0.1610)	(0.1654)	(0.1766)
Vicinity 1.4-1.6 km	0.0140	-0.1275	-0.1317
	(0.1198)	(0.1246)	(0.1319)
Vicinity 1.6-1.8 km	-0.2101	-0.1389	-0.0678

	(0.1587)	(0.1506)	(0.1297)
Vicinity 1.8-2 km	0.0522	-0.0546	-0.0442
	(0.0560)	(0.0583)	(0.0618)
Vicinity 2-2.2 km	0.0352	-0.0777	-0.0776
	(0.0995)	(0.0930)	(0.0954)
Vicinity 2.2-2.4 km	0.0021	-0.1013	-0.0727
	(0.1596)	(0.1585)	(0.1668)
Vicinity 2.4-2.6 km	-0.2277	-0.2921	-0.3366
	(0.2405)	(0.2200)	(0.2405)
Vicinity 2.6-2.8 km	0.1343	0.0283	-0.0321
	(0.1241)	(0.1248)	(0.1197)
Vicinity 2.8-3 km	0.0882	0.0182	0.0181
	(0.0743)	(0.0722)	(0.0749)
Vicinity 3-3.2 km	0.3370***	0.2557***	0.2418**
	(0.0797)	(0.0752)	(0.0784)
Vicinity 3.2-3.4 km	0.3270***	0.2514**	0.2278*
	(0.0924)	(0.0910)	(0.0913)
Vicinity 3.4-3.6 km	0.0248	-0.0887	-0.0999
	(0.1177)	(0.1098)	(0.1127)
Vicinity 3.6-3.8 km	0.3407***	0.2318***	0.2335***
	(0.0664)	(0.0649)	(0.0659)
Vicinity 3.8-4 km	0.1182	0.0169	0.0177
	(0.0740)	(0.0741)	(0.0756)
Vicinity 4-4.2 km	0.1759***	0.0746	0.0624
	(0.0493)	(0.0481)	(0.0511)
Population density			1.3820
			(1.8265)
Personal income per capita ($)			0.0008
			(0.0009)
Observations	280,164	280,164	271,680
R-sq	0.107	0.180	0.181
Building age control	Yes	Yes	Yes
Property FE	Yes	Yes	Yes
Month-by-sample FE	Yes	Yes	Yes
Year FE	Yes	No	No
County-by-year FE	No	Yes	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 (3), the average housing price premium for houses from CCUS is 4.14%.

Supplementary Note 4: Treatment-Control Comparison Using Potential CCUS Sites

To address the potential bias arising from CCUS projects' proximity to existing industrial facilities, we conduct an additional analysis using a new control group. First, for each CCUS project site, we identify two similar existing industrial facilities of the same type (e.g., power plants) located in the same state but without a CCUS project within 20 km. Second, we designate these industrial facilities as potential CCUS sites and select transactions within 4.2 km of these potential sites to form a new control group. Lastly, we re-estimate our difference-in-differences (DID) models using this new control group and compared the results with our original findings.

This approach ensures greater comparability between treatment and control groups in terms of exposure to nearby industrial facilities. **Supplementary Table 9** provides information on each selected control site, including its location, the paired CCUS site, and the basis for similarity.

Supplementary Table 9. Control site information.

Controlsite	Latitude	Longitude	Pairccus	Similarity	Nearestccus	Km2ccus
ExxonMobil Beaumont Refinery	30.07	-94.08	site1	Refinery in Texas	site1	30.8
LyondellBasell Matagorda Complex	28.79	-95.94	site1	Chemical plant in Texas	site30	92.3
Tinsley Oil Field	32.70	-90.46	site10	Oil field in Mississippi	site10	150.4
Yellow Creek Oil Field	31.76	-88.75	site10	Oil field in Mississippi	site31	136.7
Ghent Generating Station	38.75	-85.04	site11	Power plant in Kentucky	site11	109.1
H.L. Spurlock Power Station	38.70	-83.82	site11	Power plant in Kentucky	site11	123.4
Yates Oil Field	30.90	-101.91	site13	Oil field in Texas	site5	530.5
Permian Basin	32.53	-94.87	site13	Oil field in Texas	site5	305.6
Chevron Phillips Chemical Cedar Bayou Plant	29.82	-94.93	site14	Chemical plant in Texas	site28	32.2
Ascend Performance Materials Chocolate Bayou Plant	28.97	-95.35	site14	Chemical plant in Texas	site30	44.9
Barry Steam Plant	31.01	-88.01	site15	Power plant in Alabama	site15	30.8
Greene County Electric Generating Plant	32.60	-87.78	site15	Power plant in Alabama	site27	159.7
Coal Creek Station	47.38	-101.16	site16	Coal-fired power plant in North Dakota	site16	52.2
Heskett Station	46.87	-100.88	site16	Coal-fired power plant in North Dakota	site16	95.8
Dallman Power Station	39.76	-89.60	site17	Power plant in Illinois	site17	63.6
Baldwin Energy Complex	38.21	-89.85	site17	Power plant in Illinois	site22	173.3
Arkalon Ethanol Plant	37.11	-100.80	site2	Ethanol plant in Kansas	site2	47.5
Sunflower Electric Power Corporation - Holcomb Station	37.94	-100.99	site2	Power plant in Kansas	site4	51.1
Harrison Power Station	39.38	-80.33	site21	Coal-fired power plant in West Virginia	site21	59.5
Pleasants Power Station	39.37	-81.29	site21	Coal-fired power plant in West Virginia	site21	72.5
Rockport Generating Station	37.93	-87.04	site22	Power plant in Indiana	site22	78.8
Warrick Generating Station	37.92	-87.33	site22	Power plant in Indiana	site22	51.4
Paradise Fossil Plant	37.26	-86.98	site23	Power plant in Kentucky	site23	52.3
Cooper Station	37.00	-84.59	site23	Power plant in Kentucky	site23	103.3
Belle River Power Plant	42.77	-82.50	site24	Power plant in Michigan	site24	298.5
Monroe Power Plant	41.89	-83.35	site24	Power plant in Michigan	site21	335.7

Mountaineer Power Plant	38.98	-81.94	site26	Coal-fired power plant in West Virginia	site26	0.9
Morgantown Energy Facility	39.64	-79.96	site26	Coal-fired power plant in West Virginia	site21	55.1
James H. Miller Jr. Electric Generating Plant	33.63	-87.06	site27	Power plant in Alabama	site27	70.4
Gadsden Electric Generating Plant	33.24	-86.46	site27	Power plant in Alabama	site27	93.5
Baytown Refinery	29.75	-95.00	site28	Refinery in Texas	site28	30.5
Pasadena Refinery	29.72	-95.21	site28	Refinery in Texas	site28	25.5
Total Port Arthur Refinery	29.96	-93.89	site30	Refinery in Texas	site1	24.1
BASF Total Petrochemicals Port Arthur	29.95	-93.89	site30	Chemical plant in Texas	site1	23.8
Choctaw Generation Facility	33.38	-89.22	site31	Power plant in Alabama	site15	117.5
Jack Watson Electric Generating Plant	30.44	-89.03	site31	Power plant in Mississippi	site31	79.4
Elm Road Generating Station	42.84	-87.83	site32	Power plant in Wisconsin	site32	33.9
South Oak Creek Power Plant	42.85	-87.84	site32	Power plant in Wisconsin	site32	34.7
San Juan Generating Station	36.80	-108.44	site33	Coal-fired power plant in New Mexico	site33	67.1
Navajo Generating Station	36.90	-111.39	site33	Coal-fired power plant in Arizona	site33	330.2
Dave Johnston Power Plant	42.84	-105.78	site37	Coal-fired power plant in Wyoming	site37	174.8
Naughton Power Plant	41.76	-110.60	site37	Coal-fired power plant in Wyoming	site37	444.0
Emporia Energy Center	38.45	-96.07	site4	Power plant in Kansas	site8	161.1
Murray Gill Energy Center	37.59	-97.42	site4	Power plant in Kansas	site8	162.3
Tolk Station	34.18	-102.57	site5	Power plant in Texas	site5	193.3
Plant X	34.17	-102.41	site5	Power plant in Texas	site5	60.9
Tecumseh Energy Center	39.05	-95.57	site8	Power plant in Kansas	site8	221.1
Nearman Creek Power Station	39.17	-94.70	site8	Power plant in Kansas	site8	246.5
Presque Isle Power Plant	46.58	-87.40	site9	Power plant in Michigan	site9	265.3
Lansing Board of Water and Light Erickson Station	42.69	-84.66	site9	Power plant in Michigan	site24	256.1

Note: Controlsite refers to the name of the site. Pairccus means the paired CCUS projects. Latitude and longitude are the coordinates. Nearestccus presents the nearest CCUS project of the control site. Km2ccus is the distance in km from the control site to the nearest CCUS project. Similarity presents the similarity between the control site and the corresponding paired CCUS site.

Supplementary Table 10 presents the DID estimation results using the new control group. The findings are consistent with our main results in direction, although the coefficient, 0.4724, is larger than our original 3.90% estimate. Large coefficients on a log outcome need to be transformed: e^coef – 1. Applying the transformation e^0.4727 - 1 = 0.6043, we find that compared to existing industrial facilities without nearby CCUS projects, having a CCUS project within 4.2 km is associated with a 60.43% increase in housing prices. This larger effect is likely due to estimating proximity effects without separating them by distance bins. We chose this approach to ensure sufficient transactions for analysis, as potential control sites were selected only if they were not within 30 km of any CCUS site to avoid the impact of CCUS projects. Analyzing in distance bins would have resulted in no observations for regression. Despite this difference in magnitude, the consistent positive direction of the effect provides additional support for our original findings. This supplementary analysis strengthens our conclusion that

CCUS projects have a positive impact on nearby housing prices, even when controlling for the presence of existing industrial facilities.

Supplementary Table 10. Treatment-control comparison: existing industrial facilities with no CCUS projects nearby as the control group.

	Outcome: Natural log of home prices (2021$)
Average housing price premium	60.43%
Coef. of D (ATT)	0.4727^{***}
p-value	0.000
Robust Std Err	0.0352
95% CI	0.4037
95% CI	0.5416
R-sq	0.226
Observations	63,859
Treated houses	6,681
Building age control	Yes
County FE	Yes
Month-of-sample FE	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. Large coefficients on a log outcome need to be transformed: e^coef – 1, as suggested by Halvorsen and Palmquist (1980). Applying the transformation e^0.4727 - 1 = 0.6043, and SE(e^β - 1) $\approx$ e^ β * SE(β) = e^0.4727 * 0.0352 = 0.0565. It means that the coefficient 0.4727 in the log-linear model translates to an approximately 60.43% effect, with a standard error of about 5.65%.

Supplementary Note 5: Robustness Check Excluding Non-Disclosure States

In non-disclosure states, real estate transactions are not disclosed and recorded, which might lead to less reliable and highly selective observations. There are 12 non-disclosure states: Alaska (AK), Idaho (ID), Kansas (KS), Missouri (some counties) (MO), Mississippi (MS), Louisiana (LA), Wyoming (WY), Utah (UT), Texas (TX), North Dakota (ND), New Mexico (NM), and Montana (MT). To ensure the robustness of our findings, we conduct an additional analysis excluding data from the five non-disclosure states in our sample: Kansas, Mississippi, Texas, North Dakota, and New Mexico.

We replicated our main model analysis, excluding 81,827 observations from the aforementioned states. **Supplementary Table 11** presents the results of this robustness check (column 2) alongside our main findings. The analysis yielded an average housing price premium of 3.95% when excluding non-disclosure states, compared to 3.90% in our main results. The coefficient for the 3 - 4.2 km vicinity remains statistically significant and positive. The overall pattern of results is similar to our main findings, indicating that the positive impact of CCUS projects on nearby property values is not driven by the inclusion of non-disclosure states. This robustness check demonstrates that our conclusions are not sensitive to the inclusion or exclusion of non-disclosure states. The consistency of results provides further support for the reliability and generalizability of our findings on the impact of CCUS projects on nearby housing prices.

Supplementary Table 11. Consistent estimation of CCUS impacts on nearby housing prices excluding non-disclosure states.

	Outcome: Natural log of home prices (2021$)	
	Main results	Results excluding non-disclosure states
Average housing price premium	3.90%	3.95%
Vicinity 0 – 1 km	-0.6851	-0.6927
	(0.6708)	(0.6681)
Vicinity 1 – 2 km	-0.1464	-0.1576
	(0.1053)	(0.1103)
Vicinity 2 – 3 km	-0.0861	-0.0936
	(0.0908)	(0.0940)
Vicinity 3 – 4.2 km	0.1560*	0.1581*
	(0.0618)	(0.0633)
Observations	264,318	212,536
R-sq	0.243	0.265
Building age control	Yes	Yes
County-level covariates	Yes	Yes
Property FE	Yes	Yes
Month-by-sample FE	Yes	Yes
County-by-year FE	Yes	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 "Average housing price premium" is calculated by averaging the non-omitted coefficients for housing price change across all properties within 4 distance bins.

Supplementary Note 6: Impact of Multiple CCUS Projects on Housing Prices

In our main analysis, we assigned each property to its nearest CCUS project site. However, we recognized that some properties might be influenced by multiple CCUS projects within close proximity. To address this, we conducted an additional analysis to account for the potential cumulative effect of multiple nearby CCUS projects on property values.

We identified several CCUS project sites within 60 miles of each other, with distances ranging from 0.75 to 59.60 miles apart:

- site1 and site14 are within 51.24 miles of each other.
- site13 and site2 are within 59.60 miles of each other.
- site13 and site5 are within 48.16 miles of each other.
- site14 and site28 are within 24.60 miles of each other.
- site15 and site31 are within 0.75 miles of each other.
- site2 and site4 are within 58.79 miles of each other.
- site24 and site9 are within 8.93 miles of each other.
- site28 and site30 are within 39.50 miles of each other.

To capture this complexity, we introduced a new variable, num_ccus_60mi, indicating the number of CCUS projects within 60 miles of each property. We also created three post-treatment variables (post1, post2, and post3) to indicate whether a transaction occurred after the operation of the nearest, second-nearest, and third-nearest CCUS projects, respectively. The num_ccus_60mi variable is dynamic, adjusting based on the operational status of nearby projects at the time of each transaction. For instance, if a house has two nearby CCUS projects but the transaction occurs before the second-nearest project's operation, num_ccus_60mi would be one.

Supplementary Table 12 presents the results of this analysis alongside our main findings. The results show that the coefficient is consistent with our main results in direction, although the average price premium is 8.32%, larger than our original 3.90% estimate. The positive impact on housing prices in the 3-4.2 km vicinity remains statistically significant. Specifically, each additional nearby CCUS project is associated with an 8.14% increase in housing prices, which is consistent with the positive impact we estimated in the main model. This supplementary analysis strengthens our conclusion that CCUS projects positively impact nearby housing prices, even when controlling for the presence of multiple projects in close proximity.

Supplementary Table 12. The impact of CCUS projects on nearby housing prices, considering the number of multiple CCUS projects.

	Outcome: Natural log of home prices (2021$)	
	Main results	Results with multiple project variable
Average housing price premium	3.90%	8.32%
Vicinity 0 – 1 km	-0.6851	-0.3707
	(0.6708)	(0.6544)
Vicinity 1 – 2 km	-0.1464	0.0128
	(0.1053)	(0.1030)
Vicinity 2 – 3 km	-0.0861	0.0763
	(0.0908)	(0.0901)
Vicinity 3 – 4.2 km	0.1560*	0.3326***
	(0.0618)	(0.0607)
Number of CCUS projects within 60 miles	N/A	0.0814*

	N/A	(0.0328)
Observations	264,318	264,318
R-sq	0.243	0.179
Building age control	Yes	Yes
County-level covariates	Yes	Yes
Property FE	Yes	Yes
Month-by-sample FE	Yes	Yes
Year FE	No	Yes
County-by-year FE	Yes	No

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 "Average housing price premium" is calculated by averaging the non-omitted coefficients for housing price change across all properties within 4 distance bins.

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