The economic consequences of carbon capture, utilization and storage projects: Evidence from housing markets in the United States and China

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The intended research questions

Carbon capture, utilization and storage (CCUS) technique serves as an important instrument to achieve decarbonization goals. As of Jan 2022, there are 38 CCUS projects that are completed, in operation, or operation in suspension in the U.S. There are 40 CCUS projects either in operation or being built as well as 36 in various stages of development in China. Despite the increasing development of CCUS projects in both countries, the costs and benefits of developing CCUS projects in local communities are **rarely assessed quantitatively**. Estimating the costs and benefits of CCUS projects presents a challenging research question with great policy relevance.

From the cost perspective, CCUS projects may bring complications to the nearby geological formations and increase the risk of complications such as earthquakes (Zoback & Gorelick, 2012, 2015). High pressurized and liquefied CO2 might cause groundwater contamination (Eldardiry & Habib, 2018) due to potential leakage during geologic sequestration that can cause potential mobilization of hazardous inorganic elements. Brine displacement may also cause water pollution (Newmark et al., 2010). CCUS in power plants may increase air pollution due to the energy penalty issue (EEA, 2011; Jacobson, 2019). It is hard to accurately quantify these geological and pollution risks and the impact of such risks on local communities due to the lack of data and causal evidence. Using high-resolution spatial data, this study estimates the impact of CCUS on the surrounding housing values in both U.S. and China. Our study provides evidence on how potential environmental and geological impacts are capitalized into the housing market to enable a more precise estimation of the local impacts of CCUS.

Our estimated impact on housing prices also incorporates potential local economic benefits. CCUS projects can reuse CO2 to enhance oil recovery and coal bed methane recovery, as well as reuse CO2 for the food industry and other industrial applications. Such increased industrial activities and output can potentially increase the local employment rate and economic activities as suggested from the evidence of other energy projects (Moreno & López, 2008; Slattery et al., 2011). In addition, CCUS may delay the retirement of coal-fired power plants, which could mitigate the economic disruptions due to the pressure of coal phase-out in the short term. These benefits may increase housing prices. Thus, our estimated impact on housing price reflects the net impacts of the benefits and costs which CCUS projects can bring to local communities.

We aim to answer the following two primary research questions:

1. *How do CCUS projects impact nearby housing prices?*
2. *How do such impacts vary by CCUS technology and socio-economic factors, and between U.S. and China?*

We will use nationwide data on existing CCUS projects in U.S. and China as well as individual-property level housing transaction prices. Our main methods will be a repeated sales or fixed effects panel regression approach, as well as a triple difference (DDD) approach. Figure 1 shows the types and distribution of current CCUS projects in China and Figure 2 shows the projects in the U.S.

The proposed work has important implications for current policy discussions around the world about the need to deploy CCUS projects at a larger scale. We aim to provide credible estimations on the local economic impacts of CCUS projects via changes in housing prices. Our results will help policymakers conduct comprehensive cost and benefit analyses of developing CCUS projects. In addition, from an efficiency perspective, our results of the heterogeneous impacts on housing markets can help policymakers optimize the siting of the CCUS projects. We focus on U.S. and China, the two largest carbon-emitting countries in the world. The results based on U.S. and China can provide broader implications for many other countries where data and estimation are not readily available. CCUS projects can also generate potential environmental and geological risks as well as the local economic benefits in other countries. We will compare the impacts of CCUS on housing prices in the U.S. and China. Such a comparison may shed light on future policy studies that examine the social and institutional barriers for deploying CCUS projects such as local attitudes towards the projects.

Contributions to the existing literature

We contribute to the literature on the value of public and environmental amenities using a hedonic pricing approach, such as the local impacts associated with public transit infrastructure, gas stations, and renewable energy projects (Hewitt & Hewitt, 2012; Yang et al., 2020; Zabel & Guignet, 2012). Hewitt and Hewitt (2012) find that there is a price premium for houses with proximity to urban rail stations. Zabel and Guignet (2012) find that gas stations can decrease nearby housing values by over 10% if leaking from underground storage tanks is observed from publicized (and more severe) sites. Similarly, shale gas development (Muehlenbachs et al., 2015), power plants (Davis, 2011), conversion of coal-fired power plants to gas-fired plants (Mei et al., 2021), and urban natural gas leakage (Shen et al., 2021) impose impacts on nearby housing values. Recent research has also explored the local impacts of renewable energy such as wind and solar projects on housing values. Although renewable energy projects generally have social benefits (e.g., mitigation of greenhouse gas emissions), studies have indicated they could lead to a reduction in house values (Dröes & Koster, 2016; Gaur & Lang, 2020; Gibbons, 2015; Jarvis, 2021) due to factors such as blocking of views and noises of wind turbines and the Nimbyism. However, no studies have focused on CCUS specifically. This proposed study fills the research gap by investigating the effect of CCUS projects

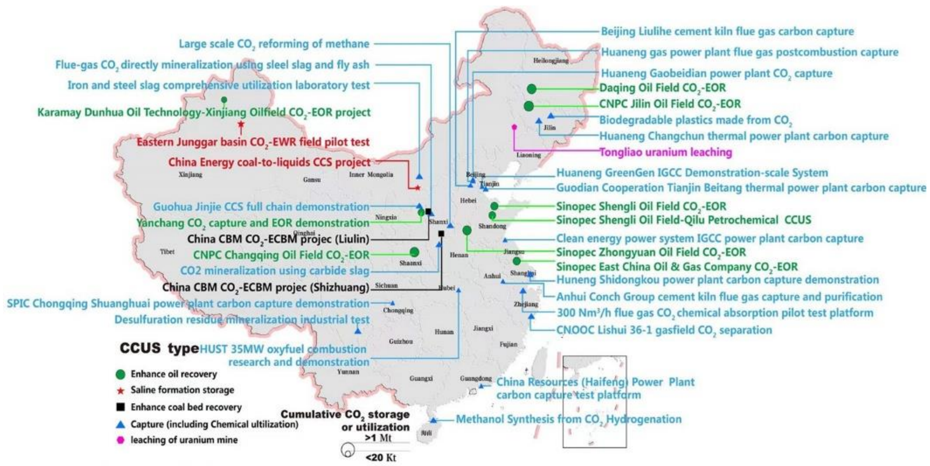

Figure 1. Current CCUS projects in China

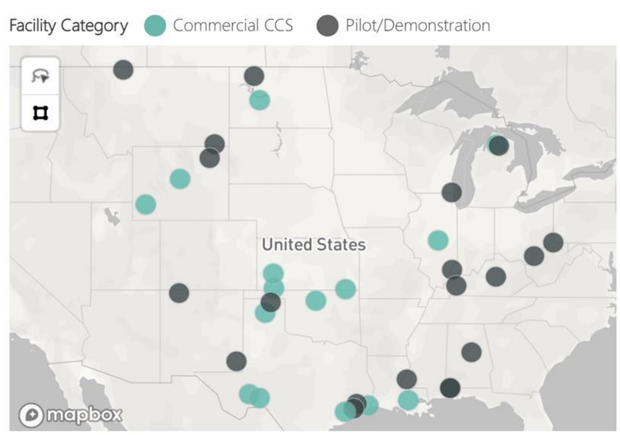

Figure 2. CCUS projects (in operation, operation suspended, or completed) in U.S.

on housing prices. Our paper also contributes to the strand of literature on public attitudes towards CCUS projects through revealed preferences. Studies have examined public perceptions of the benefits, costs, and risks of CCUS projects in China (Liu et al., 2021) and Germany (Linzenich et al., 2019, 2021) via surveys. The evidence of how individuals' preference towards CCUS projects is mixed (Sun et al., 2020). Our study will help inform effective expansion of CCUS projects, as possible opposition from residents may lead to problems as we have witnessed in expanding wind and solar projects (Carlisle et al., 2015).

Research design and approach

- Summary of empirical strategy

We will conduct analyses separately for U.S and China, and then compare the results between the two countries. Our main methods are a fixed-effects panel regression approach as well as a DDD approach. A cross-sectional hedonic pricing approach may suffer from potential endogeneity issues. The estimation of the impact of CCUS projects on property values can be confounded by the following issues. The selection of a CCUS project site may not be exogenous and can be correlated with the property values. For example, the CCUS projects might be more likely to be located in areas with low or high property values. There might be omitted variable bias. Unobservable factors such as local attitudes towards CCUS and climate change, and local government's incentives for infrastructure development, can impact both the CCUS development and housing prices. In addition, there may be other contemporaneous changes during the CCUS project development (but are not a result of the CCUS project) that can also impact local housing prices, such as the development of other nearby infrastructure projects. The fixed effects panel regression approach can eliminate time-invariant property-level unobservables that are correlated with CCUS project development, such as local attitudes towards and incentives in place for energy and infrastructure projects as well as baseline property values.

We will first conduct an event study analysis at the zip code level to test whether the parallel trend assumption is satisfied between the houses within the vicinity of CCUS and those without. We will follow recent advancements in event study models and parallel trend assumption testing techniques (Freyaldenhoven et al., 2021; Marcus & Sant'Anna, 2021; Roth, forthcoming). Specifically, we plan to check the pre-treatment trend to see if, before the treatment, the difference between the treatment and control group (without vicinity of CCUS) is constant over time.

- Fixed effects panel regression

The main <u>individual house level</u> fixed effects panel regression model is specified as follows

$$logY_{ict} = \beta_1 \sum_b^{10} Vicinity_{ictb} * Post_{ictb} + \beta_2 Post_{ict} + \boldsymbol{X'_{it}\theta} + \varphi_c * \omega_y + u_i + \gamma_m + \varepsilon_{ict} \quad ,$$

where $\log Y_{ict}$ is the natural logarithm of the sales price of house i at day t in county c. $Vicinity_{ictb}$ is the treatment variable and equals 1 if a house i has a CCUS within a certain distance bin b and 0 otherwise. For example, we can use distance bins in the range of 0 to 2 km with a 0.1km increment. Our choices of the distance range and the bin width follow prior studies on the effects of wind and solar projects (Jarvis, 2021; Keith et al., 2021) and shale gas (Muehlenbachs et al., 2015) on housing prices, where they find most of the effects are limited to 1 or 2km. We will try different ranges and bin widths to find the limit of the effects of typical CCUS projects. $Post_{ictb}$ equals 1 if the CCUS is within distance bin b and is after the CCUS construction completion date, and 0 otherwise. u_i controls for individual fixed effects, capturing all the time-invariant individual building specific characteristics. $\varphi_c * \omega_y$ represents county-by-year fixed effects, capturing unobservable common features in each year of each county, such as changing local housing market conditions, land cost, service area population, and road traffic flow. γ_m includes the month of the year fixed effects. We will also try other sets of time fixed effects such as month-of-sample fixed effects. In addition, we will try an alternative model specification with group-specific time trends to help address the potential problem of contemporaneous changes (Davis et al., 2014). ε_{ict} is an idiosyncratic error term. $\boldsymbol{X_{it}}$ controls for local demographics and economic conditions. We cluster our standard errors at the individual house or CCUS project level, allowing for correlations between observations within the same house or CCUS project. Recent papers show that using two-way fixed effects model to estimate treatment effects may be biased if the treatment timing varies across groups (e.g., de Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021). We will use the methods suggested by recent papers to check and address this potential bias. For China, we will conduct the analysis at the apartment building level due to the lack of individual housing transaction data, following Mei et al. (2021).

In terms of the timing of treatment, we will add different timing indicator variables such as 6 months, 1 year, and 2 years prior to the start of CCUS operation to examine whether the construction period also has any impact on nearby housing prices. We will also try an alternative method of dropping the data during the construction period to only look at the impact of operation. For example for U.S. CCUS projects, we can drop the data during the start year of operation.

We further apply the propensity score matching (PSM) method and the recent synthetic difference-in-differences (DID) method (Arkhangelsky et al., 2021) to establish an alternative control group. PSM accounts for the covariates that predict the treatment status so that bias caused by confounding factors can be reduced. After matching, for each house with a CCUS project in proximity (treated), we find a control house in the same zip code that is comparable on all observed covariates but does not receive the treatment. Examples of the matching variables include year built, number of stories, number of bedrooms, number of rooms, land value, and square footage.

- Tripple difference (DDD)

For the types of CCUS projects that are added to existing industrial sites (such as CCUS used for enhanced oil recovery (EOR) and for power plants), we apply a DDD approach to further control for any differential trends as well as potential contemporaneous changes between control and treatment groups. This approach compares housing prices of buildings in close proximity to a CCUS project (i.e., within treatment buffer zone) to those further away, around the CCUS and non-CCUS sites, and before and after the operation of CCUS projects. For example, for EOR CCUS projects, we compare the treatment and control houses of EOR projects before and after the start of CCUS, as well as compare the "treatment" (within the treatment buffer zone of non-CCUS operational oil fields) and control houses of non-CCUS oil fields. Then we compare the difference between the two DIDs.

- Heterogeneity of price premium

The price premium induced by vicinity to CCUS projects may be heterogeneous across different local socioeconomic characteristics and by different CCUS technology types and project sizes. We explore the heterogeneity by several key factors such as environmental awareness, income per capita, CCUS production size, and technology type. Following Shen et al. (2021), we employ a flexible semiparametric approach for the fixed effects panel data model, which has advantages in estimating non-linear heterogeneity by allowing for linearity in some variables while non-linearity in others (Cai et al., 2019). In addition, we will compare the results between U.S. and China.

- Robustness check – Cross-sectional hedonic approach

The repeated sales approach relies on intertemporal price variation. However, if the hedonic gradient shifts over time, this approach could be biased (Kuminoff & Pope, 2014; Muehlenbachs et al., 2015). To address this issue, we will conduct a cross-sectional hedonic analysis as a robustness check. The houses with CCUS projects within the vicinity of a certain range (for example, 0.5-0.6 km) are matched with houses without CCUS within 1 km (or another range depending on the range we find from our panel regressions). Treated houses in other distance bins are removed for a cleaner analysis. Then we apply a propensity score matching on the time-invariant building characteristics which are correlated with the house prices (Qiu et al., 2017).

Lastly, to explain the results, we will also look at how CCUS development is associated with changes in local economic activities such as employment and health indicators.

Data available to answer the research questions

CCUS project data-China: *Annual report on carbon dioxide capture, utilization and storage (CCUS) in China (2021) – Study on the path of CCUS in China* (available at http://www.caep.org.cn/sy/dqhj/gh/202107/t20210725_851241.shtml) describes the information about the start time for operation (including day, month and year), type, and detailed location of each CCUS project. There are about 40 CCUS projects being in operation or under construction in China, with a total capture capacity of 3 million tons per year. We only consider carbon capture projects and carbon source reprocessing projects, not including geological storage projects, because they are in remote areas where housing transactions rarely happen. Our final dataset contains 12 carbon capture projects and 2 carbon source reprocessing projects.

Housing data-China: We have secured housing price data from CityRE (www.cityre.cn), a commercial property data company that maintains a database of more than 90% of China's housing transaction records since 2005. As individual real estate transaction records across China are unavailable, our analysis relies on the average transaction price per square meter at the apartment building level of a residential complex, similar to the JEEM paper by Mei et al. (2021). Though the data is subpar compared to the individual-housing transaction data, it is enough to offer significant variation and is superior to other hedonic studies in China that apply city-level or provincial-level housing transaction data. Specifically, our unit of observation is the average transaction price, rather than rental rate, of all home sales in an apartment building of a complex in a given quarter. After dropping apartment buildings 10 kilometers outside of a CCUS project, we have a sample of housing sales in 4594 residential complexes from 14 cities across China. The data also contains information about the developer, year built, and average square footage of an apartment, as well as specific geographic coordinates.

CCUS project data-U.S.: The Global CCS Insitute (https://co2re.co/FacilityData) contains the project level information for all CCUS projects in the U.S., including the first year in operation, technology details, ownership, facility category (commercial or demonstration), facility industry (natural gas processing, power generation, hydrogen production, fertilizer production, refining, ethanol production, etc), and facility location. We analyze the projects that are completed, in operation, or operation in suspension, a total of 38 projects as of 2021. These are the projects that were put into operation. In total, there are 21 projects in operation as of 2021, 15 projects completed, and 2 projects' operations in suspension.

Housing data-U.S.: The research team has access to Zillow's ZTRAX data for this project. While the ZTRAX program will end in 2023, we can still use the data for this project according to the existing agreement. We have obtained 4TB of data for more than 150 million homes in 51 states from Zillow. Our dataset includes information from more than 374 million detailed public transaction records since the 1900s to present across over 2,750 counties for residential and commercial properties. The data also include property assessment information such as property and building characteristics, property addresses, and prior assessor valuations of approximately 200 million parcels in over 3,100 counties, via twice-a-year independent property assessments.

Conflict of interest (COI) statement: No members of the research team have ties to the energy industry. There are no other potential conflicts.

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