# Government financing and innovation crowding-out in the EU Carbon Capture sector

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**Abstract**

This paper explores the interplay between government subsidies for projects and private innovation within the Carbon Capture and Storage (CCUS) sector, particularly focusing on how regional sectoral integration and concentration influence innovation output. Regions with integrated industrial sectors feature higher openness and more partnerships, and are expected to utilize sector-specific funds more efficiently, fostering innovation. Conversely, concentrated sectors, with strong barriers to entry, might reduce innovation efforts to maximize profits from existing technologies. To investigate these hypotheses, sectoral integration and concentration indexes for the CCUS industry are computed using various economic indicators at the EU regional level. A Poisson panel regression analysis is employed to test the association of these factors with innovation output. The results indicate that while the effect of concentration is generally insignificant, sectoral integration positively influences innovation. However, when considering non-linear interactions with policy incentives, the data reveals a nuanced picture: higher number (and magnitude) of policy incentives tend to crowd out private innovation in concentrated sectors, whereas they stimulate innovation in highly integrated sectors. These findings highlight the importance of sectoral structure in shaping the effectiveness of industrial policy to foster innovation. Moreover, to take care of potential endogeneity in the announcement of policy, an event-study design is employed. Results suggest a crowding-out effect of project subsidies on the level of innovation.

**Keywords:** eco-innovation, carbon capture & storage, green transition, industrial organization

**JEL Codes:** O14, Q52, L13

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Mistakes are mine.

# 1 Introduction

This paper examines the economics of Carbon Capture and Storage (CCUS), a rapidly emerging (though not completely novel) technology that has garnered significant investments but still requires substantial resources to reach commercial viability. CCUS is considered a potential game-changer for the green transition in hard-to-abate industries (Dalla Longa et al., 2020;[11] Lau, 2021;[23] Paltsev et al., 2021[34]). Despite its premise, CCUS technologies are often unprofitable when aimed solely at reducing emissions due to the lack of a robust $CO_2$ market[1] to make large-scale CCUS projects financially viable. Consequently, governments heavily subsidize the development of CCUS projects and hubs. For instance, the EU has allocated more than USD 2 billion through the Innovation Fund and Connecting Europe Facility programme (IEA) specifically to CCUS projects. On top of that, national governments also provide substantial funding for the development of new projects[2].

This context brings to the main question of the paper, namely: what is the consequence of highly subsidizing long-term projects on the innovation output, and furthermore, how this effect is moderated by the sectoral structure at regional-level. This paper posits that government funding for CCUS projects might crowd out private innovation, particularly in regions with fewer firms relative to projects in the sector (i.e., more *concentrated*). In such cases, firms may prefer to leverage existing technologies to secure tenders and maximize profits rather than investing in new innovations. Conversely, in more *integrated* sectors — i.e., with higher levels of cooperation, a greater number of active firms, and more projects — the crowding-out effect might be mitigated. The involvement of diverse players competing for tenders could stimulate innovation despite substantial government financing.

The economic literature has extensively highlighted the importance of knowledge exchange among industry stakeholders (Audretsch 1996,[5] Sonn & Storper, 2008[45]). According to Porter (1998),[38] "Clusters are geographically proximate groups of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities". The local agglomeration of specialized firms has been associated with higher innovative output (Moreno et al., 2006).[28] However, not all technologies share the same market characteristics. Eco-innovations, in particular, are doomed with the double externality problem, where private returns from innovation are significantly lower than social returns. Moreover, highly technical and hardly scalable innovations often involve risks and costs that likely deter private investment without government intervention.

[1] the creation of which the European Union is aiming for, as witnessed by the adoption of the Industrial Carbon Management Strategy (COM/2024/62) in early 2024.

[2] e.g., SDE++ scheme assigned USD 7.3 billion to CCUS projects in the Netherlands; £1 billion by UK Carbon Infrastructure Fund.

In this perspective, government financing can have either a stimulating effect ("crowding-in") or a negative effect ("crowding-out") on private investment in innovation. The evidence on whether government financing crowds in or crowds out overall private innovation is inconclusive (see Petrin, 2018 for a review).[36] The presence of crowding-in or crowding-out effects depends on various factors, including the specific characteristics of the innovation market, firm-level attributes (Popp & Newell, 2012),[37] and the type of government policy enacted (Friedman, 1978[15]). This paper aims to contribute to this ongoing debate by exploring the impact of government subsidies for projects on innovation output in a specific technologyFurthermore, I use regional-level data and indices to test the hypotheses.

To this aim, this paper proceeds by analyzing the impact of announcing national level subsidies for the development of carbon capture and storage projects on the regional level of innovation in the period 2000-2022 in the Euro Area. Besides year fixed effects and standard regional-level controls such as real GDP per capita and industry-level wages, I use EU regional innovation score to control for the quantity and quality of overall innovation and two measures of specific sector concentration and integration. Lacking information on specific R&D expenditures I employ (priority) patents filed as a second-best solution to proxy specific innovation effort in the dependent variable. Results show that the announcement of policies (and their weight in financial terms) has a negative overall effect, that becomes positive only for well-integrated regions. Higher government-backed budgets for CCUS projects crowd-out innovation output in concentrated regions, suggesting that companies strategically decrease innovation effort to maximize returns from established innovations in a less-competitive environment. Sectoral integration has a strong positive baseline impact on patenting levels, while the interaction with the announced budget is positive, suggesting a crowding-in effect. Results hold when pre-sample mean is introduced to account for unobserved heterogeneity in technology-specific capacity at regional level. Furthermore, to address endogeneity concerns, an event-study excludes possible anticipation effects in the announcement of subsidies.

# 2 Literature review

## 2.1 Competition and innovation incentives

Innovation literature managed to investigate the best competitive conditions in which innovation might flourish, also considering the role of government. In general, according to the Schumpeterian hypothesis, concentration (i.e., higher market power) is associated with higher levels of innovation, since competition reduces expected rents, discouraging new entries in the market (Romer,1990;[42] Aghion and Howitt, 1992[1] and Grossman and Helpman, 1991[16]). This phenomenon is known as "appropriability issue" and it was confirmed by some empirical literature (see Levin & Reiss, 1984[24]). Its solution has been envisaged into the application of intellectual property rights. These tools - exemplified by patents in the case of technology - give to the innovation owner's the possibility to fully or partially (see Arrow, 1973,[4] and Levin, 1988[25]) exclude others from exploiting its idea, creating the necessary incentive to invest in the first place. However, the role of competitive pressure on innovation is still debated. Aghion et al. (2005)[2] theorize and test the hypothesis of an inverse U relationship between competition and innovation which depends on the technology state of different firms. Their model and results show that the standard Schumpeterian effect (i.e., disincentivized entry of new innovators) between laggards and leaders is accompanied by an increased innovation output due to the necessity of similarly advanced firms to compete with one another in order to win the market. Similarly, much of the empirical literature found that competitive pressure may in facts lead to more innovation (see Blundell, Griffith & Van Reenen, 1999;[8] Beneito et al., 2015[6]). In this perspective, the seminal work of Vives (2008) gives insights with respect to the importance as to how we measure competitive pressure. A standard measure is the number of firms participating to the market, even if the relationship among these firms might not be purely competitive. Innovation literature widely recognized the value of spillovers and knowledge recombination in quality and quantity of innovation, which grow in the number of firms. In particular, regional clusters are expected to have positive influence on innovation, thanks to the scaled productivity gains for the participants (Porter, 1980)[39][3]. Feldman (1999)[14] conducts a review of empirical studies on the topic and concludes that knowledge spillovers following geographical proximity (e.g., industrial or technological regional clusters) have positive impact on the innovation output. Oerlemans (2001)[31] finds that complexity of the underlying innovation is key to push for inter-organisational linkages at a cluster level. The linkages can range from more or less involuntary spillovers to actual R&D joint ventures[4], as in Kamien et al. (1992),[21] where these are found to yield the highest consumer surplus provided firms don't collude at the production stage[5]. In this sense, a more integrated market likely helps increasing overall innovation output. In summary, the interaction between integration, competitive pressure and market concentration has no ascertained unique effects, rather these depend on the context and features of the market.

One further element of the picture concerns the nature of eco-innovations, whose Carbon Capture & Storage technologies may be defined an example of. Besides the usual appro-

[3]See also the book by Vom Hofe[49]

[4]Joint ventures at the R&D stage exploits the benefit of vertical integration, before competing in the market for products. See Perry, 1989[35]

[5]See also Karbowski & Prokop, (2019)[22] for a similar result.

priability issue, eco-innovations bear a further burden, fore they bring with them social benefits (in terms of positive spillovers due to smaller environmental costs as compared to competitors) which outweigh private ones. This is known as the double-externality problem (Rennings, 2000).[41] Moreover, some innovations may be harder, if not impossible, to market. This could be due to not advanced enough technological readiness, or long-run required investment; leading us to the logical conclusion that in absence of consistent expected profits, no innovation is undertaken.

## 2.2 Government intervention and *crowding-in vs. crowding-out*

To finance innovation, subsidies in the R&D stage are the most commonly resorted tool, delivering best effects when addressed to private - rather than cooperatively set - R&D (Hinloopen, 2001).[18] Furthermore, subsidies are more efficient when given to basic R&D, with respect to applied, due to the higher expected spillovers. Government intervention in R&D procurement raises the question of the extent to which such intervention stimulates greater research effort by private entitites (i.e., crowding-in) or, conversely, replaces it (i.e., crowding-out). Evidence is mixed, with studies finding no crowding-out effects (Hottenrott & Rexhäuser, 2015);[19] crowding-in effects subsequent to policy intervention in the provision of a public good in presence of complementarities with other products sold by firms (Reisinger et al., 2014);[40] or both effects (Damrich et al., 2022).[12] The debate around crowding-in and crowding-out effects extends to the macroeconomic origin of the terms and their reprise in applied microeconomic literature, often leading to potential confusion. Deleidi, Mazzucato, & Semieniuk (2020)[13] argue that these terms, when used in sectoral innovation studies, may be inappropriate. They contend that crowding effects are inherently aggregate phenomena, typically associated with the potential effects that expansionary fiscal policy can have on output (Blanchard, 2017[7]). In contrast, government intervention in a specific sector aims to correct market failures as a primary rationale. In this sense, crowding-out wouldn't be possible in the first place. This critique is focused on the impact of public intervention on private investment, the primary lens through which these effects are studied.

While this paper is not an event study and does not estimate a direct replacement (i.e., crowd-out) effect, it considers the timing dimension in innovation dynamics. Here, "crowding out" refers to the sector-specific innovation that a quasi-monopolist firm may forgo when it receives direct investment to build a plant using established technologies which are already available.

This dynamic trade-off between the immediate need to build CCUS plants and pursuing efficiency-enhancing innovation for the future is often overlooked in industrial policy studies and is derived from timing and research effort (or innovation quality) trade-off, typical of R&D races and tournaments literature[6].

I consider previous findings and characteristics of CCUS market to select key features to model the dynamics of integration and competitive pressure on the level of innovation in the next sections.

# 3 Data

## 3.1 Regional-level data

Data at regional level (NUTS2) have been downloaded and systematized from different institutional databases. Real GDP, population, employment (total and by sector), wages (total and by sector), hours worked (total and by sector) and general expenditure in R&D (total and by sector of performance) were retrieved on Annual Regional Database of the European Commission (ARDECO) and Eurostat. All countries from the European continent for which available data was available have been considered for this study. In particular, the presence of Turkey, Norway and Switzerland justifies the introduction of a dummy variable to control for countries belonging to the EU after the CCUS directive of 2009. In addition, European Regional Innovation Scoreboard was downloaded from the official dashboard available at the EU commission site. Only values since 2016 were available on the platform; hence, values before 2016 were manually retrieved from official reports and systematized in a single dataset, adjusting for different scoring techniques indicated in each report. Final RIS data range between 2000 and 2022, with missing observations and significant difference between observations reporting the actual score and the ones reporting the categorical performance evaluation. Patent data was retrieved thanks to OECD *Regpat* database (OECD, 2008[27]). Only EPO filings were filtered by technology-specific IPC and CPC codes; then, they were summed at regional level basing on the inventors' region and priority year, as standard practice in patent literature, in order to avoid the inclusion of lower-quality patents and the home-bias (OECD, 2009[26]). It's important to note that OECD *Regpat* database only considers patents belonging to families of at least two, in order to exclude lower quality filings. Number of inventors was also retrieved from patent data and aggregated at regional and year level. Finally, data on CCUS projects were retrieved and aggregated from different sources (mainly, the IEA CCUS database and Clean Air Task Force CCUS database). The two sources were aggregated (to remove double counted projects) and each project was identified

[6]See the seminal papers by Nalebuff & Stiglitz (1983)[29] or Taylor (1995),[47] covering role of information rank in R&D tournaments

and geolocalized based on information available in the dataset and on the web. Thanks to geospatial data on NUTS3 polygons provided by the European Commission, it was possible to translate coordinates into NUTS3 regions. Capacity of each project was summed at regional and year level and added to the dataset. Reference year for projects is announcement year.

## 3.2 Firm-level data

*Regpat* list of applicants was used to retrieve European firms patenting in CCUS sector; the resulting list was eventually aggregated at NUTS level to represent the number of active firms in the sector each year. Particularly, this measure was achieved by considering any firm that patented at least one CCUS innovation as *active* from the patenting year onwards. By matching *Regpat* firms with Orbis through HAN names retrieved from OECD *HAN* database, associated ISIN codes were used to retrieve number of joint ventures, strategic alliances and R&D agreements from the Eikon Refinitiv database. This indicator adds to the set used to build sector integration index and proxies the openness of the system.

## 3.3 Policy data

Policies were retrieved by IEA official CCUS policy database. This database provides detailed information about policies at national and supranational level for World countries. Among the others, it features the country and region of application, the policy type (e.g., *"grants"*, *"payments and transfers"*, *"regulation"*), technologies considered (e.g., *"Direct Air Capture (DACC)"*, *"Enhanced Oil Recovery"*), policy status (*"in force"* or *"announced"*) and the public amount budgeted for each measure. For the sake of this study, it was important to have information on whether and when a certain financing policy was announced, with the amount budgeted upfront, in order to infer on the potential incentive for innovators and players in the sector[7]. A total of 55 policy interventions for the CCUS sector have been carried out by governments in the European region since 2000. All financing policies were manually updated with announced budget and registered at national level basing on announcement year. Regulation policies were subtracted to the total to derive a final number of incentive policies (under the form of public funding, fiscal incentives or other form of payments). The sum of budget at national level was computed and normalized to PPP.

Two main (alternative) explanatory variables were derived from this database: *"Pol-*

[7]As examples: the "UK Plan for Jobs - Direct Air Capture" set out in 2020, allocated £100 million for DACC R&D and projects; the "Danish CCUS Fund" in Denmark gathers more than $3 billion, with an expected $100 million disbursement every year since 2025.

*icy_budget_cum"*, equal to the cumulative sum of financing announced by the government in each country allocated to CCUS projects; *"Policy_quantity_cum"*, equal to the cumulative sum of the number of policies. The budget variable is more complete, hence it has been used in the main results, while the alternative variable is employed in the robustness checks available in Appendix A. As a further robustness, the analysis has been run with a standard annual 10% rate depreciation of the budget variable.

# 4 Descriptive statistics and variables construction

## 4.1 Sector integration

CCUS sectoral integration composite index was computed on the basis of regionalized firm-level information. The index was computed by means of a principal component analysis (PCA) following other examples available in the literature (Zhang et al., 2015;[50] Volosovych, 2012[48]). In particular, to correct for higher correlation among some components, I applied a two-step PCA procedure, following Chen & Boo (2010).[10] This index aims at considering the overall development and integration of the CCUS sector at regional level by considering different aspects related to the entire supply chain. Variables used were: number of active firms in the sector (*cum_act_firm_std*), computed as cumulative sum of companies that patented a CCUS invention starting in the patenting year onwards; number of partnerships (*partner_std*), computed as the yearly sum of joint-ventures and strategic alliances by each CCUS firm in any given year; number of projects (*project_std*), as the yearly sum of projects, and number of firms (*cum_n_partners_std*) involved in each projects; cumulative sum of announced sequestration capacity (*cum_proj_capacity_std*); and finally, cumulative sum of CCUS hubs (*cum_hubs_std*), a governance structure for the aggregation of different projects and partners. Since these variables have mostly heterogeneous units of measures, they were all standardized. The final index is normalized by year to a scale between 0 and 1.

| 1st step | 2nd step |
|---|---|
| project_std | |
| cum_proj_capacity_std | |
| cum_hubs_std | |
| cum_n_partners_std | |
| | cum_act_firm_std |
| | partner_std |

Table 1: *CCUS sector integration index pca procedure*

## 4.2 Concentration

Concentration measures generally consider the number of participants to a market and their relative market share. The case of CCUS is an example of a market with no traditional product competition, hence making it hard to compute a standard Herfhindal Index. To measure concentration at regional level, scores were created for each region in each year with respect to variables of interest at sample-level (cumulative number of projects or hubs, cumulative regional capture capacity, cumulative number of participating or absolute number of active firms[8]). In this way, each region is scored relatively to all the other ones for any given year. Secondly, to have the regional concentration index for region$i$ at time $t$ I summed the scores relative to projects, hubs and capacity and divided by the sum of the scores of project partners and innovating firms. Similarly to integration, the measure was normalized to a scale between 0 and 1 based on year.

$$Concentration_{it} = \frac{\epsilon + cum\_n\_project + cum\_capacity + cum\_n\_hubs}{\epsilon + cum\_n\_partners + n\_active\_firms} \tag{1}$$

A higher value for this index indicates that the CCUS sector for the region in that year is more concentrated (i.e., lower number of firms relatively to projects).

In the following figure 1 a comparison of the concentration and sector integration indexes (period mean) mapped at EU NUTS2 level:

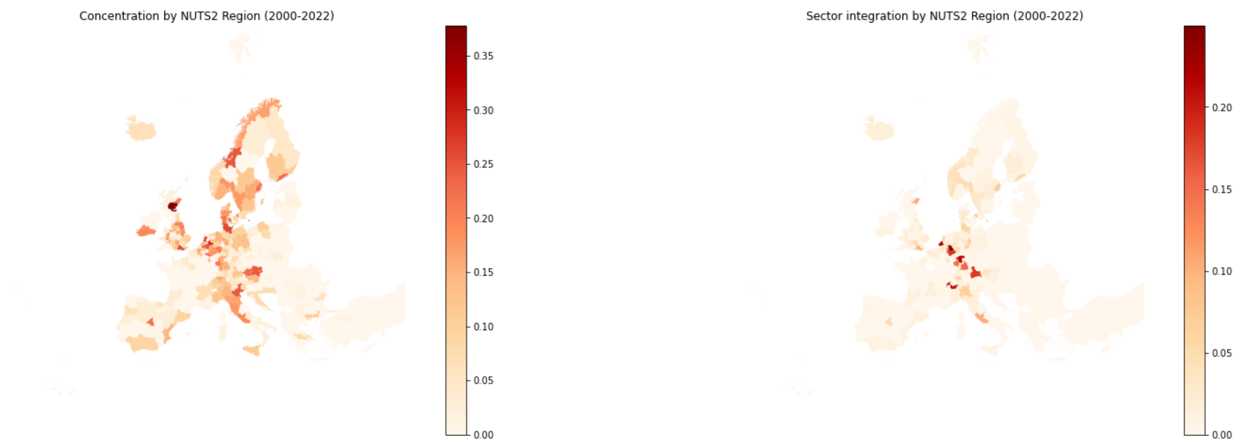
As expected from a sector like CCUS, where entry costs are high and expected profits are very low since they are mostly depending on public financing, the level of concentration is diverse and averagely high, while sector integration is lower on average. These results indicate that, on average, each project has a limited number of participants, and firms in the sector have limited partnerships as well. Note that, by limitation due to variable availability, the integration index only proxies the overall openness and development of the sector at regional level, but cannot inform on the specific intra-sector relationships.

Regarding the time trend of concentration and integration indexes, their behavior is quite diverse (see figure 2): in facts, (mean) concentration starts high and quickly decreases after the introduction of the EU CCUS directive in 2009; this is probably due to the higher supply of projects announced and financed by the European government.

Instead, (mean) sectoral integration does not show the same stark response to the intro-

[8]The choice to use absolute number of active firms in each year - as opposed to the cumulative number of projects and partners - derives from the construction of the *active_firms* variable: a firm is considered active, and counted as one in each year departing from the first filed innovation. Using the cumulative sum would have artificially inflated the count. Variables such as project number or project partners are instead unique to the year of announcement, but since the time-span for projects is heterogeneous and averagely above the 6-7 years, the cumulative sum of these variables is used to account for the longer term persistence of the effects.

Figure 1: *CCUS concentration and integration means for period 2000-2024 at NUTS2 level*




(a) Concentration

(b) Sectoral integration

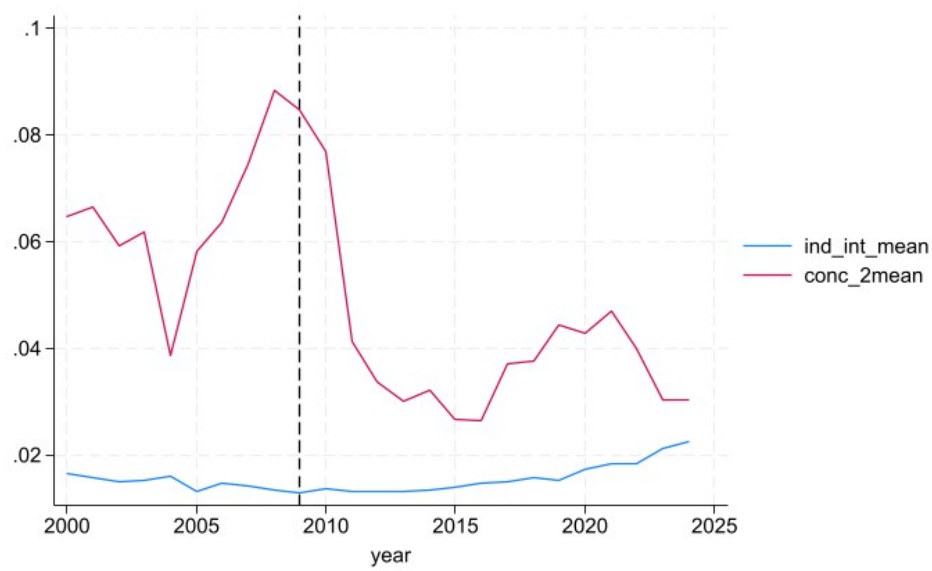



Figure 2: *Mean concentration and sectoral integration (2000-2024).*

duction of the directive, rather featuring a small increase during the years, likely due to the average project dimension (in terms of capacity and number of partners) not increasing too much after the directive.

# 5 Empirical strategy

In the innovation literature, when working with patent data as dependent variable, Poisson models are the appropriate choice in that they can handle integer, non-negative values. Particularly, to estimate the impact of policy, concentration and integration variables on the level of innovation I employed a Poisson pseudo-maximum likelihood estimator, capable of handling excessive zeroes and computationally efficient (Silva & Tenreyro, 2006;[44] 2011[43]). I also apply the pre-sample CCUS mean (Blundell, 2002[9]) computed at the regional-level to capture potential unobserved heterogeneity across groups in specific innovation capacity (Orsatti et al., 2024;[32] Noailly & Smeets, 2015;[30] Barchi & Rondi, 2024). This decision is due to the implicit correlation between at least one of the regressors (regional innovation score), which partially depends on past realizations of the dependent variable, CCUS patents. Besides, another reason to not employ standard unit-level fixed effects (excluding pretedermined variables) is due to the low within variability of the main explanatory variables *integration* and *concentration*, which would be mostly absorbed by the fixed effects returning unreliable coefficients. The baseline model follows this form:

$$E(Pat_{it}|inc_{it-1}, conc_{it-1}, int_{it-1}, \gamma X_{it-1}, \nu_t, \eta_i, \mu_{it}) = \lambda_{it} \tag{2}$$

such that:

$$\lambda_{it} = \exp\left(\beta_0 + \beta_1 inc_{it-1} + \beta_2 int_{it-1} + \beta_3 conc_{it-1} + \gamma X_{it-1} + \nu_t + \eta_i + \mu_{it}\right) \tag{3}$$

where the main explanatory variables are the logarithm of cumulative funds from announced incentive policies, the level of concentration and sectoral integration in each region $i$ at time $t-1$. Following, the vector $X_{it-1}$ contains a set of variables to control for structural economic and innovation indicators (real GDP per capita, real wage in the industry sector, a dummy for the 2009 EU CCS directive and the European Commission's regional innovation score). $\nu_t$ represents year fixed effects, $\eta_i$ is the pre-sample mean estimator and $\mu_{it}$ is the error term. Standard errors are clustered at country level to allow for spillover effects across regions (Orsatti et al., 2020).[33] The model is also augmented with the interactions between specific policy budget and concentration or integration, as well as non-linear budget impact (see table 3).

The final panel covers data for 17 countries at NUTS2 disaggregation level between 2000 and 2024.

## 5.1 Results

Following, the results in table 2 of the poisson regressions. Model (1) is the baseline specification, while model (2) and (3) introduce interaction between *integration* and *concentration*. Model (4) presents both interactions. Models (5) to (8) add pre-sample specific patenting variable mean as a unit level fixed effect.

Table 2: *Poisson pseudo-maximum likelihood regression results*

| CCUS_pat | (1) base_sq | (2) conc | (3) ind_int | (4) both | (5) base_sq_fe | (6) conc_fe | (7) ind_int_fe | (8) both_fe |
|---|---|---|---|---|---|---|---|---|
| L.Policy_budget_cum | -0.0426 | -0.00862 | -0.118*** | -0.0965*** | -0.0412* | -0.0120 | -0.119*** | -0.0987*** |
| | (0.146) | (0.761) | (0.000) | (0.000) | (0.085) | (0.635) | (0.000) | (0.000) |
| L.Concentration | 0.718 | 0.956*** | 0.722 | 0.969*** | 0.504 | 0.708*** | 0.509 | 0.721*** |
| | (0.111) | (0.007) | (0.116) | (0.005) | (0.118) | (0.004) | (0.129) | (0.003) |
| L.Integration | 7.254*** | 7.183*** | 7.185*** | 7.103*** | 1.458 | 1.504 | 1.216 | 1.262 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.673) | (0.660) | (0.721) | (0.710) |
| L.Policy_budget_cum#L.Concentration | | -0.189*** | | -0.217*** | | -0.155*** | | -0.177*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| L.Policy_budget_cum#L.Integration | | | 0.599*** | 0.668*** | | | 0.672*** | 0.709*** |
| | | | (0.000) | (0.000) | | | (0.000) | (0.000) |
| Perf_score (Leader) | 1.109** | 1.151** | 1.083** | 1.112** | 1.400*** | 1.430*** | 1.369** | 1.385*** |
| | (0.019) | (0.015) | (0.025) | (0.021) | (0.008) | (0.006) | (0.010) | (0.009) |
| Perf_score (Strong) | 0.934** | 0.972** | 0.917** | 0.939** | 1.024** | 1.057** | 1.000** | 1.020** |
| | (0.018) | (0.013) | (0.022) | (0.018) | (0.014) | (0.010) | (0.017) | (0.014) |
| Perf_score (Moderate) | 0.516 | 0.511 | 0.511 | 0.504 | 0.607* | 0.601* | 0.602* | 0.593* |
| | (0.137) | (0.134) | (0.144) | (0.144) | (0.085) | (0.085) | (0.090) | (0.092) |
| EU_policy_dummy | 1.929*** | 1.660*** | 1.644*** | 1.152*** | 1.642*** | 1.510*** | 1.270*** | 0.982*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.004) |
| GDP_pc_new | 36.12** | 37.01** | 36.20** | 37.35** | 13.32 | 14.32 | 13.39 | 14.73 |
| | (0.037) | (0.032) | (0.040) | (0.032) | (0.573) | (0.542) | (0.575) | (0.535) |
| Industry_wage | 2.66e-05 | 2.58e-05 | 2.69e-05 | 2.60e-05 | 3.40e-05** | 3.34e-05** | 3.44e-05** | 3.38e-05** |
| | (0.188) | (0.198) | (0.183) | (0.193) | (0.013) | (0.014) | (0.011) | (0.012) |
| Observations | 2,467 | 2,467 | 2,467 | 2,467 | 2,365 | 2,365 | 2,365 | 2,365 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Pre_sample_CCUS | | | | | 0.570*** | 0.559*** | 0.578*** | 0.567*** |
| r2_p | 0.442 | 0.446 | 0.445 | 0.449 | 0.482 | 0.484 | 0.485 | 0.488 |
| N_clust | 17 | 17 | 17 | 17 | 17 | 17 | 17 | 17 |

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Results from the cross-sections in models (1) to (4) show that public subsidies to CCUS projects is generally associated with a decrease in sector-specific innovation. The effect is not significant unless the interactions with *integration* and *concentration* are added, suggesting that there is no linear effect. In this context, sectoral *integration* shows a positive impact on innovation; furthermore, the effect is increasing in the budget allocated for project, indicating that this kind of eco-innovation strongly benefits of wide market participation and higher levels of openness (i.e., more projects, partnerships and hubs) to contrast crowding-out. Contrarily, *concentration* does not seem to have significant impacts on the level of innovation. Its effect becomes significant as soon as non-linearity is introduced, showing a small and positive effect of *concentration*. Nevertheless, the interaction coefficient with public project financing is significant and negative, suggesting that higher subsidies in concentrated markets are associated with lower levels of innovation. Results in models (5) to (8) considers pre-sample CCUS innovation mean as a fixed effect controlling for the innovation capacity at region level. Interestingly, the EU 2009 policy dummy has strong and significant coefficient in all the results. Results are mostly confirmed except for baseline sectoral integration which loses significance, probably due to its small over-time variation.

In table 3 I run the same models introducing a non-linear interaction in the budget variable.

Table 3: *Non-linear policy budget interaction*

| CCUS_pat | (1) base_sq | (2) conc | (3) ind_int | (4) both | (5) base_sq_fe | (6) conc_fe | (7) ind_int_fe | (8) both_fe |
|---|---|---|---|---|---|---|---|---|
| L.Policy_budget_cum | -0.326*** | -0.289*** | -0.0473 | 0.696*** | -0.278*** | -0.261*** | 0.116 | 0.878*** |
| | (0.000) | (0.000) | (0.703) | (0.000) | (0.001) | (0.002) | (0.455) | (0.000) |
| L.Policy_budget_cum#L.Policy_budget_cum | 0.0132*** | 0.0130*** | -0.00384 | -0.0456*** | 0.0110*** | 0.0115*** | -0.0130 | -0.0563*** |
| | (0.000) | (0.000) | (0.625) | (0.000) | (0.005) | (0.002) | (0.147) | (0.000) |
| L.Concentration | 0.720 | 0.960*** | 0.719 | 0.972*** | 0.504 | 0.712*** | 0.498 | 0.725*** |
| | (0.106) | (0.006) | (0.117) | (0.005) | (0.115) | (0.004) | (0.142) | (0.003) |
| L.Integration | 7.276*** | 7.196*** | 7.181*** | 7.078*** | 1.489 | 1.521 | 1.185 | 1.204 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.668) | (0.657) | (0.729) | (0.723) |
| L.Policy_budget_cum#L.Concentration | | -0.188*** | | -0.283*** | | -0.156*** | | -0.249*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| L.Policy_budget_cum#L.Integration | | | 0.679** | 1.834*** | | | 0.953*** | 2.153*** |
| | | | (0.015) | (0.000) | | | (0.000) | (0.000) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,467 | 2,467 | 2,467 | 2,467 | 2,365 | 2,365 | 2,365 | 2,365 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Pre_Sample_CCUS | | | | | 0.568*** | 0.558*** | 0.581*** | 0.570*** |
| r2_p | 0.443 | 0.447 | 0.445 | 0.450 | 0.482 | 0.485 | 0.485 | 0.489 |
| N_clust | 17 | 17 | 17 | 17 | 17 | 17 | 17 | 17 |

Robust pval in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In the second set of results, the non-linear public financing variable gives apparently ambiguous answers: in model (1) - (2) and (5) - (6), the baseline variable is negative while the squared term is positive, suggesting a crowding-out effect, that is decreasing depending on the amount invested. When all the interactions are considered (model (4) and (8)) the baseline variable becomes positive and the squared term negative. The sign shift is due to the introduction of the interaction terms, which changes the interpretation of the base incentive variable[9]: in regions having the same levels of concentration and sectoral integration, a higher public budget to finance projects is associated with a (marginally decreasing) rise in innovation. In this final model, this positive (crowding-in) effect is enhanced by sector integration and limited by concentration. Significance tests on interaction coefficients in models (4) and (8) reject the null hypothesis that they are equal to zero. Results are robust to i) a different public financing variable (i.e., cumulative number of incentives); ii) a yearly depreciating (10%) subsidy variable.

# 6 Endogeneity concerns

A key concern in my empirical setting is the potential endogeneity arising from simultaneous shocks that could influence both government subsidies for CCUS projects and CCUS innovation output. Even if several factors mitigate this issue (regional and year fixed effects, controls for trends in industry and a dummy for CCUS EU policy of 2009) the core concern remains: the endogeneity of government subsidies and innovation. Specifically, simultaneous shocks—such as broader EU industrial policy shifts may drive both the decision to allocate subsidies and the observed innovation outcomes, raising concerns about the causal interpretation of the relationship with the announcement of subsidies.

To identify the effect of CCUS funding announcements on regional innovation, I estimate an event–study specification following the interaction weighted estimatori from Sun and Abraham (2021).[46] The model compares regions that received their first CCUS funding policy[10] in a given year (treatment cohort) with regions that were not yet treated or never treated. [11]. This estimator is a useful alternative to the standard two-way fixed effects estimator, in case of heterogenous effects of treatments. Since policies are different across the various countries and regions, both in terms of regulation and subsidy magnitude, this estimator is more appropriate in this situation. The regression includes region and year fixed effects as well as the usual set of controls (*Real per capita GDP*, *regional innovation score*, *wages in the industrial sector*, *dummy for CCUS EU policy*, *regional concentration* and

[9]see Aiken et al., 1991[3]

[10]Note that I consider every possible kind of policy regarding projects - not only direct financing - in order to capture the earliest possible shock.

[11]Stata command *eventstudyinteract*. See Sun, L. (2021). Eventstudyinteract: Interaction weighted estimator for event study. URL: https://github. com/lsun20/eventstudyinteract.

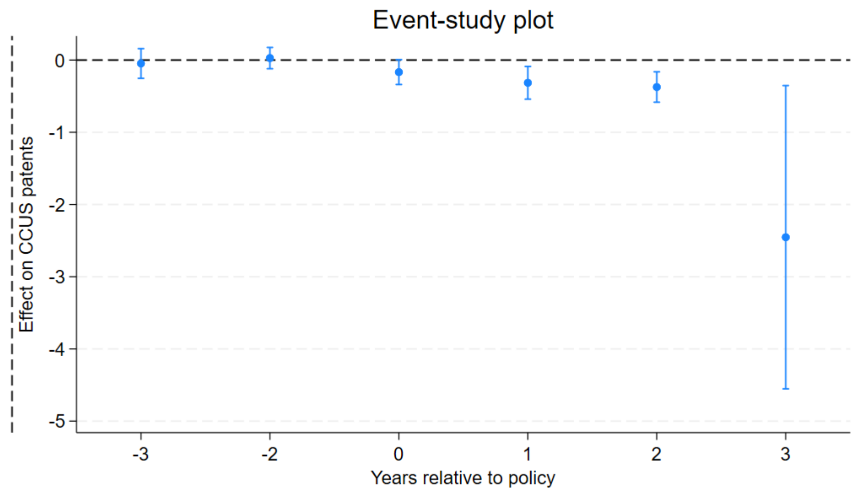



Figure 3: Event-study results. Year -1 is the baseline year.

*regional integration*). I include leads and lags of the treatment indicator relative to the year before the first policy announcement, which is omitted as the baseline. The lead coefficients serve as placebo tests: if they are statistically indistinguishable from zero, this supports the parallel trends assumption. The lag coefficients trace the dynamic treatment effect in the years after the announcement, showing whether innovation increases, decreases, or remains unchanged compared to the pre-treatment trajectory.

Results (see Figure 3) show that trend in patenting is decreasing and significant one, two and three years after the introduction of the first incentive policy, while it is non-significant (i.e., thus satisfying pre-trends assumption) the three years before the introduction of the policy.

In particular, the contemporaneous effect (t=0) is negative and marginally significant at the 10 percent level, indicating a slight drop in CCUS patenting in the announcement year. This negative effect becomes larger and statistically significant in the subsequent years: patenting declines by roughly 0.3 applications one year after treatment, by 0.37 applications after two years, and by more than 2.4 applications after three years. These results point to a strong crowding-out effect: instead of stimulating innovation, policy financing appears to reduce patenting activity in regions where projects are announced. The absence of significant pre-trends supports a causal interpretation of these negative post-treatment dynamics.

# 7 Conclusion

This paper analyzed the impact of public financing on innovation within the EU's carbon capture and storage (CCUS) sector, focusing on the moderating effects of sectoral integration and concentration. The results reveal a nuanced relationship between public subsidies and innovation output, shaped by the structural characteristics of the regional CCUS market. Following, I discuss the main results.

First, the overall association between public subsidies announcement and specific innovation is positive. This finding is shared by the literature on fiscal incentives and firm innovation, which is generally agreeing on positive effects of incentives depending on firm size, sector and type of instrument [12]. Importantly, the findings underscore the role of non-linearities in financing, with diminishing returns as funding increases, this being a rather novel addition to the literature. Second, the relationship between public subsidies and regional innovation is mediated by the structure of the market. In particular, regions featuring higher sector integration benefit of the development and enhanced openness and collaboration, further improving their innovation output associated with the incentives. Conversely, more concentration (i.e., fewer firms controlling the majority of projects) is associated with a negative significant impact of project subsidies on patent output (i.e., crowding-out). This findings suggest that a gatekeeping role is played by big companies in concentrated regions, securing public money to run big projects and at the same time reducing own private R&D investment in the field. This indicates that the effectiveness of public subsidies hinges on their alignment with market structure.

Finally, an event study was carried out to isolate the causal impact of subsidies on the level of innovation, to address concerns of potential endogeneity in the main explanatory variable. The pre-tends parallel assumption is confirmed by the result, suggesting that a direct effect of the subsidies for project is indeed present. In particular, this impact seems overall negative and small for the first two periods, while it decreases dramatically in the third year.

The implications for policymakers are clear: to foster innovation in the CCUS sector, public funding strategies should prioritize integration by incentivizing partnerships, joint ventures, and hub-based governance models. These mechanisms not only broaden participation but also counterbalance the potential gatekeeping effects observed in concentrated markets. Additionally, the findings highlight the importance of tailoring financing instruments to regional market structures, as blanket approaches may inadvertently suppress innovation in less competitive environments.

[12] see Hu et al., 2019[20] and Guceri & Liu, 2019[17] for comprehensive reviews

This study contributes to the literature by offering a sector-specific analysis of how public financing interacts with structural market features to influence innovation. However, it is not without limitations. The absence of firm-level intra-sector relationships and the reliance on patent counts as proxies for innovation limit the scope of conclusions. Future research could address these gaps by exploring direct measures of R&D collaboration and innovation quality. Moreover, extending the analysis to other green technologies could validate whether the observed dynamics are unique to CCUS or represent broader patterns in eco-innovation sectors.

By emphasizing the interplay between public policy and market structure, this paper provides actionable insights for designing effective industrial policies. As the CCUS market evolves, rather than relying solely on subsidies, policymakers should foster competitive and integrated markets to enhance innovation. Policies that encourage partnerships, joint ventures, and open-market participation may prove more effective in sustaining long-term technological progress. Achieving this is critical not only for the green transition but also for ensuring that the CCUS sector remains a vibrant driver of innovation in the broader decarbonization agenda.

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# Appendix A

In table 4 I show results using the cumulative number of policy interventions by region, instead of the cumulative sum of allocated budgets. This variable allows to use all available observations, also the ones for which the budget of the CCUS subsidies was not found.

Table 4: *Alternative policy variable: Poisson pseudo-maximum likelihood regression results*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| CCUS_pat | base_sq | conc | ind_int | both | base_sq_fe | conc_fe | ind_int_fe | both_fe |
| L.Policy_quantity_cum | -1.002* | -0.685 | -1.793*** | -1.970*** | -0.951** | -0.690 | -1.932*** | -2.011*** |
| | (0.051) | (0.184) | (0.000) | (0.000) | (0.021) | (0.109) | (0.000) | (0.000) |
| L.Concentration | 0.721 | 0.944*** | 0.699 | 0.965*** | 0.506 | 0.692*** | 0.476 | 0.715*** |
| | (0.108) | (0.009) | (0.138) | (0.006) | (0.115) | (0.005) | (0.174) | (0.004) |
| L.Integration | 7.258*** | 7.195*** | 7.214*** | 7.101*** | 1.466 | 1.518 | 1.230 | 1.228 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.671) | (0.658) | (0.719) | (0.719) |
| L.Policy_quantity_cum#L.Concentration | | -1.496*** | | -2.040*** | | -1.197*** | | -1.707*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| L.Policy_quantity_cum#L.Integration | | | 8.572* | 12.68*** | | | 11.20*** | 14.09*** |
| | | | (0.053) | (0.000) | | | (0.000) | (0.000) |
| Perf_score (Leader) | 1.109** | 1.153** | 1.078** | 1.102** | 1.399*** | 1.431*** | 1.358** | 1.369*** |
| | (0.019) | (0.014) | (0.027) | (0.022) | (0.008) | (0.006) | (0.011) | (0.009) |
| Perf_score (Strong) | 0.934** | 0.973** | 0.910** | 0.928** | 1.023** | 1.058** | 0.988** | 1.003** |
| | (0.018) | (0.013) | (0.024) | (0.020) | (0.014) | (0.010) | (0.019) | (0.016) |
| Perf_score (Moderate) | 0.515 | 0.510 | 0.513 | 0.500 | 0.606* | 0.599* | 0.605* | 0.591* |
| | (0.138) | (0.136) | (0.143) | (0.149) | (0.086) | (0.086) | (0.089) | (0.095) |
| EU_policy_dummy | 1.844*** | 1.579*** | 1.872*** | 1.321*** | 1.558*** | 1.422*** | 1.506*** | 1.130*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.002) |
| GDP_pc_new | 36.12** | 36.89** | 35.87** | 37.20** | 13.33 | 14.19 | 12.81 | 14.49 |
| | (0.037) | (0.032) | (0.040) | (0.033) | (0.573) | (0.545) | (0.593) | (0.541) |
| Industry_wage_ | 2.66e-05 | 2.58e-05 | 2.69e-05 | 2.61e-05 | 3.40e-05** | 3.34e-05** | 3.46e-05** | 3.39e-05** |
| | (0.189) | (0.199) | (0.183) | (0.193) | (0.013) | (0.014) | (0.011) | (0.012) |
| Observations | 2,467 | 2,467 | 2,467 | 2,467 | 2,365 | 2,365 | 2,365 | 2,365 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Pre_sample_CCUS | | | | | 0.569*** | 0.560*** | 0.581*** | 0.569*** |
| r2_p | 0.442 | 0.446 | 0.444 | 0.449 | 0.482 | 0.484 | 0.484 | 0.488 |
| N_clust | 17 | 17 | 17 | 17 | 17 | 17 | 17 | 17 |

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Furthermore, I consider a yearly depreciation of announced subsidies over a period of 10 years to allow for more variability (Table 5). Results hold.

Table 5: *Poisson pseudo-maximum likelihood regression results with yearly depreciating subsidies*

| CCUS_pat | (1) base_sq | (2) conc | (3) ind_int | (4) both | (5) base_sq_fe | (6) conc_fe | (7) ind_int_fe | (8) both_fe |
|---|---|---|---|---|---|---|---|---|
| L.Policy_budget_dep | 0.194** | 0.190** | 1.855*** | 2.152*** | 0.166** | 0.160** | 1.849*** | 2.104*** |
| | (0.026) | (0.032) | (0.000) | (0.000) | (0.029) | (0.048) | (0.000) | (0.000) |
| L.Policy_budget_dep#L.Policy_budget_dep | -0.00904** | -0.00837* | -0.115*** | -0.132*** | -0.00795** | -0.00730* | -0.115*** | -0.130*** |
| | (0.036) | (0.068) | (0.000) | (0.000) | (0.036) | (0.093) | (0.000) | (0.000) |
| L.Concentration | 0.734* | 0.756* | 0.748* | 0.783* | 0.513 | 0.533* | 0.525 | 0.558* |
| | (0.100) | (0.090) | (0.096) | (0.069) | (0.105) | (0.099) | (0.108) | (0.072) |
| L.Integration | 7.227*** | 7.218*** | 7.088*** | 7.078*** | 1.432 | 1.429 | 1.128 | 1.129 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.680) | (0.679) | (0.741) | (0.740) |
| L.Policy_budget_dep#L.Concentration | | -0.0534 | | -0.138*** | | -0.0401 | | -0.114*** |
| | | (0.300) | | (0.000) | | (0.488) | | (0.001) |
| L.Policy_budget_dep#L.Integration | | | 3.881*** | 4.474*** | | | 3.981*** | 4.489*** |
| | | | (0.000) | (0.000) | | | (0.000) | (0.000) |
| Perf_score (Leader) | 1.125** | 1.134** | 1.035** | 1.036** | 1.416*** | 1.423*** | 1.319** | 1.321** |
| | (0.018) | (0.017) | (0.033) | (0.032) | (0.008) | (0.007) | (0.015) | (0.014) |
| Perf_score (Strong) | 0.949** | 0.959** | 0.859** | 0.859** | 1.039** | 1.047** | 0.939** | 0.941** |
| | (0.016) | (0.015) | (0.035) | (0.034) | (0.013) | (0.012) | (0.027) | (0.027) |
| Perf_score (Moderate) | 0.520 | 0.520 | 0.505 | 0.497 | 0.610* | 0.610* | 0.597* | 0.591* |
| | (0.132) | (0.130) | (0.152) | (0.157) | (0.082) | (0.081) | (0.095) | (0.098) |
| EU_policy_dummy | 1.627*** | 1.718*** | 2.055*** | 2.391*** | 1.493*** | 1.557*** | 1.922*** | 2.188*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| GDP_pc | 36.30** | 36.32** | 37.02** | 37.05** | 13.50 | 13.53 | 14.10 | 14.16 |
| | (0.035) | (0.035) | (0.035) | (0.034) | (0.567) | (0.566) | (0.557) | (0.554) |
| Industry_wage | 2.66e-05 | 2.66e-05 | 2.72e-05 | 2.71e-05 | 3.40e-05** | 3.40e-05** | 3.47e-05** | 3.47e-05** |
| | (0.188) | (0.189) | (0.183) | (0.183) | (0.013) | (0.013) | (0.011) | (0.011) |
| Observations | 2,467 | 2,467 | 2,467 | 2,467 | 2,365 | 2,365 | 2,365 | 2,365 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Pre_sample_CCUS | | | | | 0.570*** | 0.569*** | 0.579*** | 0.577*** |
| r2_p | 0.442 | 0.442 | 0.447 | 0.447 | 0.481 | 0.481 | 0.487 | 0.487 |
| N_clust | 17 | 17 | 17 | 17 | 17 | 17 | 17 | 17 |

Robust pval in parentheses

*** p<0.01, ** p<0.05, * p<0.1