What drives the success or failure of CCU projects?*

Antonio Barchi† Marco Illich‡ Riccardo Monaco§ Laura Rondi¶

November 1, 2025

Abstract

Carbon Capture (Usage) and Storage are key technological options to mitigate CO_2 emissions. They can be applied to many different sectors, mainly highly polluting ones. This paper studies what factors drive the technological progress and the success of Carbon Capture and Utilization (CCU) projects by focussing on organizational structure – vertical integration, product diversification and partnerships – ownership and environmental policy as drivers of successful completion. CCU projects capture the CO_2 for direct reuse in industrial processes or as a feedstock to produce chemical components, sustainable cement, polymers, fertilizers, e-fuels. Thus, CCU can be a lever for industrial decarbonization and meets more favourable public perception and acceptance than CCS. We construct a dataset of CCU projects, and we estimate what project characteristics are associated with higher Technology Readiness Level and advancement. Then we use survival analysis to study what affects the probability that the project reaches its expected objective. Our results show that the structure and organization of the project -namely, the interaction between vertical integration, diversification and partnership size - as well as the environmental policy – particularly, public incentives to low carbon R&D expenditures - affect the technological progress and the probability of success of CCU projects.

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

JEL Codes: O14, Q52, L13

Acknowledgments.

*This manuscript is part of the project NODES SPOKE 2 – Green technologies and Sustainable industries, which has received funding from the MUR – M4C2 1.5 of PNRR funded by the European Union - NextGenerationEU (Grant agreement no. ECS00000036).

†Politecnico di Torino

‡Politecnico di Torino

§Politecnico di Torino

¶Politecnico di Torino

1 Introduction

Carbon Capture Usage and Storage (CCUS) - a unifying expression for CO_2 Capture and Storage (CCS) and CO_2 Capture and Utilization (CCU) - is viewed as an important technological option to mitigate CO_2 emissions. It can be applied in many ways and to many different sectors, mainly those that are highly polluting, such as the energy sector. As the International Energy Agency states in its report "CCUS in Clean Energy Transitions" (IEA, 2020), CCUS will contribute almost 15% of the cumulative reduction in emissions from the energy sector by 2070. Although CCS and CCU are often grouped under the more general label CCUS, these two technological families are very different in terms of climate impact, underlying scientific know-how, and potential applications (Bruhn et al. (2016)).

This paper provides an updated project landscape, following their evolution, diffusion, status and technological variety of applications, and then studies what factors drive the technological progress and the success of CCU projects.

CCU projects capture CO_2 for direct reuse (after appropriate treatment) in other industrial processes or in downstream applications aimed at producing chemical components that are valuable to many industries. In turn, these by-products can be used for the manufacture of sustainable cement, polymers, or fertilizers. Alternatively, the captured CO_2 may be directly utilized as a feedstock for electro-fuels (e-fuels). Thus, CCU can be a significant lever for industrial decarbonization, facilitating the transition toward a more efficient and sustainable low-carbon economy, in which CO_2 is reintegrated into production cycles rather than being simply stored. For this reason, interest in CCU is steadily increasing—both within the scientific community, as shown by the growing number of patents and publications (Nawaz et al., 2022 , ITUL et al., 2023), and among industrial producers, who understand how the reuse of CO_2 can favour the creation of new products and materials as a means to diversify revenue streams and enhance the economic sustainability of their business.

In addition, although CCU is still in an earlier stage of development, compared to CCS, and with far fewer projects, it seems to have more favorable public perception and acceptance than CCS. For example, Arning et al. (2019) find that the driving causes of positive perception, in addition to the climate mitigation effects of CCU, are the savings of fossil resources and the lower dependence on them. Thus, CCU – the usage of captured CO_2 - has a higher perception of benefits and a lower perception of barriers than CCS, the capture and storage of CO_2. A further reason might be the track record of CCS projects, as it is increasingly recognized that their deployment has been slow, difficult and irked with failures (Wang et al., 2021, Abdulla et al., 2020, Agency, n.d.). In contrast, the effectiveness of the deployment of CCU projects has not received the same attention by the literature and therefore specific evidence on the success or failure of these projects is still scant.

This awareness motivates our research, which differs from other studies on CCUS projects (Wang et al., 2021, Abdulla et al., 2020, Agency, n.d.) in that we: i) focus on CCU projects, ii) investigate the project characteristics driving their "success", i.e., the ability to realize their goal and/or become operational, not their failure, and iii) we highlight the impact of their organizational structure We draw on the economic and environmental literature to find the factors that can affect or impair the technological progress and the realization of research-intensive and high-cost projects such as these. Assuming that technological progress and commercial feasibility, as measured by their Technological Readiness Level (TRL) is one driver of the probability of success, we identify three additional domains of influence, potentially contributing to project completion: structure (vertical integration and product diversification) and organization (extension of the partnerships); source of financing (ownership), and (environmental) policy.

To perform the empirical analyses, we construct a dataset of CCU projects using several sources (IEA, CO2 Value Europe, DAC Coalition, project website), then we estimate what project characteristics are associated with a higher Technology Readiness Level and with its change within the project duration and we study what affects the probability that the project reaches its expected target using survival analysis. Our results show that the structure and organization of the project, as well as the environmental policy - particularly public incentives to low carbon R&D expenditures - do affect the technological progress and the probability of success of CCU projects. The paper is organized as follows. Section 2 presents the background literature from which we derive our conceptual framework. Section 3 describes the data and the main characteristics of CCU projects. Section 4 presents the empirical strategy and the main results. Section 5 concludes.

2 Related literature and conceptual framework

2.1 The evidence on CCUS projects

The empirical evidence on Carbon capture, utilization and storage (CCUS) projects is inconclusive, as it shows that many initiatives struggle to reach successful completion and many others have been terminated or put on hold before achieving operational status (Hepburn et al., 2019; Agency, n.d.; Mac Dowell et al., 2017;Abdulla et al., 2020; Memon et al., 2024; Barchi et al., 2024). These studies highlight that large investments requirements, insufficient funding, low or negative internal rate of returns, policy uncertainty and high hurdle rates contribute to the unsatisfactory success record of CCUS projects (Colombe et al., 2024).

They also reveal that each CCUS project appears as a unique, first-of-a-kind venture that meets significant engineering and execution impediments, when standardized solutions or economies of scale cannot be achieved. Common causes of failure include challenging technical scale-up and fragile commercial viability, suggesting that even if the technology works, the business model is undermined by cost overruns or insufficient revenue streams. Successful cases are few, often made possible by readily deployable applications that leverage existing infrastructure without requiring cross-sectoral investments. A typical example is CO_2 injection in EOR practices, which naturally allows immediate economic returns.

A thorough analysis by Wang et al. (2021) on 263 CCUS projects (1995–2018) has found that 78% of large-scale projects (i.e., with capacity $\geq$0.3 Mt CO_2/year) were canceled or suspended. The study applies survival analysis to estimate the likelihood of projects' failure and focuses on the impact of technology push and market pull policies. Results show that large plant size, as measured by CO_2 capture capacity, increases the hazard rate while government ownership, a business-driven market (such as E.O.R.) and a tax credit policy reduce it. In short, past projects have shown that without strong supportive policies, the likelihood of failure remains a major concern (see also Zhang et al., 2025).

2.2 Background literature and conceptual framework

The empirical results on CCUS projects suggests that more focused evidence is needed on CCU initiatives, as they cover, by definition, the final stage of the value chain by bringing to the "market" the captured CO_2. In our study, we investigate the role of the technological readiness level of these projects and their organizational structure, carbon utilization, and governance characteristics. Our research thus differs from Wang et al. (2021) also because we employ survival analysis to estimate the probability of project success, rather than their failure. We then consider the impact of specific policy actions aimed at promoting decarbonization.

Several project characteristics are likely to influence the technological advancement and the probability of success of CCU projects.

Empirical evidence suggests that bridging the gap between pilot scale and full commercial scale requires significant support (financial and organizational) and learning-by-doing to pass through the "valley of death" in technology development (Nemet et al., 2018). Thus, as CCU/CCS projects imply very complex technologies (Nath et al., 2024) that depend on the results of scientific research, the ability to reach the expected Technological Readiness Level (TRL) can contribute to success (Abdulla et al., 2020). On the one hand, small or experimental projects at low initial TRL may have a scientific objective that aims at a given

TRL, not to become operational, or may fail in their infancy due to greater uncertainty (ITUL et al., 2023). On the other hand, projects with a higher initial TRL often rely on more mature, pilot-tested technology, face lower technical risks and thus have a better chance to reach implementation.

Budget size and public or private origin of financing are also expected to be key drivers. CCU projects are capital-intensive, so adequate funding must be secured to carry the project through R&D, engineering, and demonstration phases. Projects with larger budgets and strong financial backing (especially those combining public and private investment) are more likely to achieve their technical milestones. A statistical evaluation of past projects found that financial factors (i.e., expected returns and risk) heavily influence project outcomes, and that existing support mechanisms have often been insufficient to mitigate risks at the scale needed (Martin-Roberts et al., 2021). In practice, many CCU pilots rely on government grants or subsidies in early stages; without continued financing into later stages through the access of follow-on capital to support the technological scale-up, they can falter once the initial funds are exhausted. On the other hand, as highlighted by Lupion and Herzog (2013), analysing the European CCS funding scheme "NER300 Programme", too much reliance on public incentives has led to a financial trap as projects did not develop their own sustainable revenue streams. A more recent study by Zhang et al. (2025) confirms that public incentives (tax subsidies and credit financing) have a positive impact on CCS captured volumes and alleviates economic duress but nevertheless may not suffice to ensure long-term success. Zhang et al. (2025) also highlights that high-intensity incentives should be provided in the early and intermediate stages of the development and then gradually reduced, in order to encourage the entry of private investors, without which it is more difficult to succeed. Finally, a careful design of public incentives is needed to avoid "rebound effects" that could reduce the environmental benefit of the projects (Jevons, 1865).

The organizational structure of the project, as proxied by the degree of vertical integration of the value chain and the number of partners involved in the project, is also expected to matter (Klein et al. (1978), Grossman and Hart (1986), Yao et al. (2018)). CCUS projects often involve multiple steps (capture, transportation, utilization or storage of CO_2), which can be managed by a single entity or by different specialized partners. The vertically integrated structure - defined by IEA (IEA, 2019) as the full-chain business model as opposed to the part-chain business model (recalling the terminology of supply-chains) - offers greater control and coordination but concentrates the burden of expertise and financing on one developer or group of companies. For example, Yao et al. (2018) shows that vertical integration is more appropriate for CCUS projects in China in early demonstration stages due to lower transaction costs. The alternative is a network structure, where different organizations handle different parts (for example, one captures CO_2, another builds the pipeline, another utilizes or stores the CO_2), also along a vertical chain. The different stages can be managed separately by different companies or coordinated within a joint venture to exploit economies of scale and risk-sharing – for instance, a shared CO_2 transport and storage network serving multiple capture sites.[1]

An organizational feature related to vertical integration is the number of partners involved, which may affect both the appropriability of the quasi-rents of the project and the coordination and monitoring costs, introducing a trade-off between the risk of entropy and the advantage from exploiting diverse skills and competences (Mowery and Rosenberg, 1991, Foray and Steinmueller, 2003, Hottenrott and Lopes-Bento, 2016). On the one hand, more partners can provide complementary expertise and resources that enhance innovation and problem-solving capacity: for example, an engineering firm, a chemical company, and a university lab each contribute specialized knowledge to different aspects of a CO_2 utilization project. On the other hand, too many partners can raise coordination costs, the potential for conflicts and the risk of appropriability of the quasi-rents (Choi and Contractor, 2019[2]). The literature suggests that effective collaborations tend to have clear task division, with each partner focusing on aspects matching their core competencies. [3]

Finally an external factors that may affct the probability of success of CCU projects is the environmental policy framework (Colombe et al., 2024, Arning et al., 2019, Fan et al., 2019). Carbon pricing mechanisms are widely recognized as a decisive external driver for CCUS deployment. Pricing CO_2 emissions (through emissions trading systems or carbon taxes) may generate an economic incentive for emitters to invest in capture and utilization, though the effectiveness of the instrument depends on price levels as well as on investment costs. For example, in the past, carbon prices under the EU Emissions Trading System were, for too long, too low to make most CC(U)S projects economically viable. Some analysts have argued that the collapse of EU ETS price in the early 2010s eroded confidence and contributed to a "lost decade" for CC(U)S investments.

[1] Many CCUS initiatives are organized within "Project Hubs", in which CO_2 is transported from different emission sources to be stored or converted using a common infrastructure. Project hubs require all partners to act in a synchronized way not to jeopardize the entire project(Barchi et al., 2024). Projects that manage this integration effectively are far more likely to succeed (Song et al. (2023)

[2] See also the article "Shaping CCUS opportunities requires diligence" (2021) by T. Jeanneret https://www.ipaglobal.com/news/article/shaping-ccus-opportunities-requires-diligence/

[3] CCUS case studies indicate that spreading project tasks across multiple organizations can provide significant insights and rapid development, such as reducing complexity for each partner and leveraging specialized capabilities, as long as the overall effort is well-coordinated (Reyes-Lúa and Jordal, 2020).The composition of the partnership should reflect an appropriate mix of skills, institutional perspectives and stakeholders' diversity aligned with the project's goals (Koelle et al., 2019).

3 An overview of CCU projects and of the data

We construct our dataset of CCU projects using information from four databases - CO_2 Value Europe; IEA Industrial CCUS Projects, IEA Demonstration Projects, DAC Coalition's Global DAC Deployments Database -, and by searching the Internet to find additional projects[4]. We obtain a population of 359 CCU projects, tracked from 2009 to 2024 (see Barchi et al., 2024 for a CCUS project landscape)[5]. The dataset is geographically polarized on the EU, where project information are more available and extensive, possibly due to a major concern about climate risks and decarbonization and discloser rules. Thus, we find that CCU projects tend to concentrate in Germany, France and Spain, and in the US (see Appendix Table 13 for a complete country list). If we look at the sources of captured CO_2 in these projects, we find that Atmospheric CO_2 (via Direct Air Carbon Capture (DACC)) is the primary source as of 2024, followed by Lime and cement, and Biogenic CO_2 (see Figure 1).

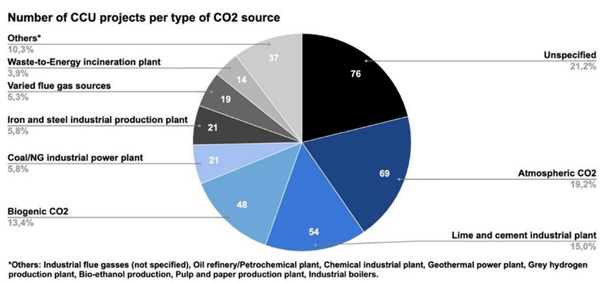

Figure 1: CCU Projects by type of CO2 source

For the empirical analysis, we collected the following project characteristics: *duration*, *status* and *facility stage*, *allocated budget*, *share of government ownership*, initial and final *Technological Readiness Levels* (*TRL*), *number of partners*, *product category* and *vertical integration*. The full list of variables and their definitions is in Appendix Table 9.

Facility stage and *TRL* are two key variables for this study. *Facility stage* can be *Planned*, *Ongoing*, *Operational* (i.e., applied projects for industrial purposes) or *Completed* (for research projects that have achieved their expected goals). Figure 2 shows that the number of CCU projects had an almost four-fold increase from 2015 to 2024, that is, after the Paris Agreement at the UN Climate Change Conference (COP21). The share of planned projects has increased from 17% (out of 223) in 2020 to 71.1% (out of 180) in 2024, while those under

[4]See the Appendix Table 8 for more detailed information and references

[5]E.O.R. projects are not included because they have long reached their commercial phase and they are mostly oriented to store underground, not use, the CO_2. If the CO_2 that returns to the surface is separated and reinjected to form a closed loop, this results in permanent storage of CO_2. Moreover, concerns seem to be widespread about the effectiveness of this technique in terms of mitigating CO_2 emissions (IEA, 2019).

construction have increased from 11.7% in 2020 to 28% in 2024, which suggests a dynamic development in the CCU sector.

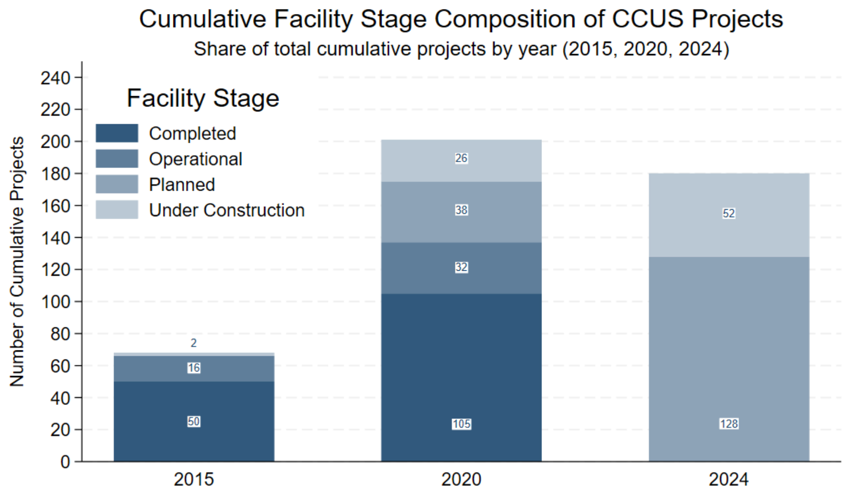

Figure 2: Projects by facility stage in years 2015, 2020, 2024.

Based on this classification, we define the binary variable *Success*, equal to 1 when the project is either *Completed* or *Operational*[6] (vis-à-vis *Planned* or *Under Construction*). *Success* combines information from the existing databases (IEA and CO_2Value) and our search on the project websites.[7]. We find that *Success* is reached by 37% of projects in the full sample, and by 39% in the final estimation sample. As a metric of technological progress, we exploit the difference between the (*TRL*) at the beginning and at the end of the projects.[8] Figure 3 shows that most projects feature a TRL around 6 and 7, indicating technologies in the demonstration stage that might soon reach the stage of commercialization (TRL 9). However, almost 23% of the projects are between level 3 and level 5 (i.e., the research and development phase), which confirms the great heterogeneity of projects and technologies. Eventually, we had to drop 24 projects that did not report the facility stage and 91 projects that do not report the budget value. The sample size further reduces to 192 due to unavailable data on the initial or final TRL and government ownership.

To measure project size, we use the *project budget* because we cannot use a typical metric like CO_2 capture capacity since most projects have no capture facilities. We then

[6]We account for the fact that research projects differ from industrial projects because when they achieve their objective, they are defined "*Completed*", as it is expected that they will become operational).

[7]Some projects had not yet completed their expected (planned) duration at the end of data collection (hence, they are censored) Their duration is calculated based on their announced start and end date. However, not necessarily a project becomes *Completed* or *Operational* by the announced end-date. In the analysis these projects are classified as *Planned* or *Under construction* (hence not a Success).

[8]Unfortunately, not all projects declare their target TRL (309) and even less their initial TRL (156).

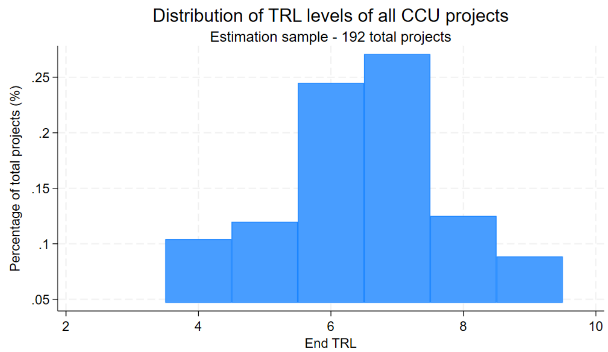

Figure 3: Distribution of TRL levels of CCU projects

account for project governance by including the share of the budget funded by public entities (*public_share*). In such innovative projects governmental agencies and supranational funding programmes are typically major partners. In our dataset, 68.7% of the projects have a public partner that provides more than 50% of the funds, with an average share of 83-84%. Overall, the public ownership share is on average 64.2%.

To account for the organization of the production process, we first add the binary variable *vertical integration*, which separates projects including the stage of CO_2 capture from those just focusing on utilization. Two thirds (66.7%) of CCU projects in our data are vertically integrated. A second key characteristic is the type and diversity of CO_2 uses, which we include to capture potential strategies of product *diversification* within the project and we measure by the number of "product categories" covered by each project. We find that most projects are specialized, as 74.5% (143) feature a single product category and only 2.6% (5) use the captured CO_2 for up to three product categories. Table 1 shows the number of projects in the estimation sample listed by number of product categories (*product_category_count*).

Number of products	Number of CCU projects
1 Product Category	143
2 Product Categories	44
3 Product Categories	5
Total	192

Table 1: Number of CCU projects by associated product category count - Estimation sample

The final uses of CO_2 from CCU projects are heterogeneous, from fertilizers and e-fuels to building materials and nutraceutical products, but ultimately they are quite concentrated as 42.2% of the projects specialize in e-fuels, 21.3% in chemical products and 23.9% in Captured CO_2 (without specifying the final use), as shown in Table 2. To account for the technological diversity of these uses, and their potential influence on success, we include them as fixed effects in the cross-section.[9]

Product Category	%	Number of CCU projects
e-Fuels	27.5 %	68
Chemicals	22.7 %	56
Captured CO_2	18.6 %	46
Building materials	6.9 %	17
Others	24.3 %	60
Total	100%	247

Table 2: Number of CCU projects by product category - Estimation sample. Each project can feature in more than one product category.

The third key feature of organization is the size of the partnership carrying out the project (*partner_count*), as we find that more than 90% count two or more partners. On average, CCU projects have 9.3 partners involved, but the number of partners is very heterogeneous, ranging from 1 to 30, with a median size of 6, which denotes a majority of small ventures. Using the Wilcoxon-Mann Whitney equality-test of medians, we find that partnerships in vertically integrated projects tend to be significantly smaller than in projects focused on utilization, whereas the size of partnership appears uncorrelated with the number of products, hence, with product diversification.

Table 3 shows summary descriptive statistics for the sample.

Var	*N*	Mean	SD	Min	p25	p50	p75	Max
success	192	.448	.498	0	0	0	1	1
duration	192	4.13	1.71	1	3	4	5	16
trl_start	101	5.3	2.06	1	4	6	7	9
trl_end	192	6.32	1.56	3	5	6	7	9
trl_adv	101	1.25	.754	0	1	1	2	3
trl_class	192	2.06	.602	1	2	2	2	3
budget	192	1.73e+08	1.01e+09	500000	3,698,046	5,974,241	1.63e+07	1.16e+10
public_share	192	.642	.331	0	.4150562	.75	.915	1
partner_count	192	9.28	6.26	1	4	9	13	30
vertical_integration	192	.667	.473	0	0	1	1	1
product_category_count	192	1.29	.505	1	1	1	2	3
long_project	192	.349	.478	0	0	0	1	1

Table 3: Summary Statistics: CCU projects - Estimation sample

Ultimately, our empirical analysis accounts for the impact of environmental policy measures that may prompt investment in CCU fundamental and applied research as well as project deployment (see also Wang et al., 2021). To this end, we extracted a sub-set of

[9]In Appendix Table 12 we report the list of all 13 product categories in the original sample as they were derived from the CO_2 Value Europe Database. We aggregate the product categories associated with the right tail of the project distribution (8 projects, 4.17% of the total) in a single category defined as "others".

indices from the OECD Environmental Policy Stringency Index (EPS) Database[10]. EPS is a country-specific index (ranging from zero to six) of environmental policy stringency that can be compared internationally. The database covers 13 policy instruments for 40 countries, from 1992 to 2020. For our analysis, we selected the overall EPS index and three sub-indices relevant in the CCU context (CO_2 Trading Schemes, CO_2 Taxes and Public Research and Development Expenditure (R&D))[11] (see Table 4).

Variable	N	Mean	Min	Max
EPS	192	3.21	.61	4.89
CO_2 Trading Scheme	191	2.02	0	3
CO_2 Tax	191	1.37	0	6
Low Carbon R&D exp.	191	2.66	0	6
tsp_start	191	2.56	0	5.5

Table 4: EPS index and sub-indexes selected for the analysis.

4 Empirical strategy and results

In this section, we use our dataset to address two research questions: which factors drive the technological advancement of CCU projects, and their successful completion. To this end, we develop two complementary empirical analyses. First, we estimate how project- and country-level characteristics affect the technological prowess achieved by each project, as measured by its final Technology Readiness Level (TRL) and by its progress during the project's duration. Second, we examine what determines the probability that a CCU project achieves its completion or becomes operational. To do so, we rely on a survival analysis framework - the accelerated failure-time model -, which allows us to identify which factors accelerate or delay project success over time.[12]

4.1 Determinants of technological level and advancement

In this first part of the analysis we use the TRL - its level at the final year of the project (Columns 1-5) and its change over its duration (Columns 6-8) - to model project technological advancement as a function of organizational factors, policy context and regional and sectoral patterns. Our specifications account for cross-spatial and cross-project differences with two

[10]https://www.oecd.org/en/publications/measuring-environmental-policy-stringency-in-oecd-countries_90ab82e8-en.html.

[11]see Kruse et al., 2022 for an in-depth look at these indices and how they are measured

[12]As an alternative approach, we also perform a logit analysis and report the results in the online Appendix.

sets of binary variables denoting either the geographical location of the project or different applications of the captured CO_2, which imply various underlying technologies. At the bottom of the table we report the p-values of tests of joint significance of the two sets of dummies as well as additional tests of potential non-linearity of the effect of organizational characteristics on the dependent variable. In Table 6, we report the results that address our RQ1.

The analysis shows that the project budget (also a proxy for size) is positively and significantly correlated with the final level of TRL, suggesting that larger projects with higher financial commitment tend to reach higher TRLs, i.e. are more likely to become closer to market exploitation. On the contrary, the public ownership share, our proxy for project governance, is negatively signed, suggesting that projects in the embryonic stages of development need a higher public share to be launched and get past technical-economic barriers.

Turning to variables describing the organizational structure, we find that vertical integration - denoting projects that capture and utilize the CO_2 - appears positively, though weakly, related with the final TRL. This may suggest that the transition to an integrated structure, at some point in the technological development of the project, may help to promote technological advancement, in line with Yao et al. (2018).The number of partners in the project is always negatively associated with the TRL, indicating that projects at early stages of technological development tend to involve many partners, maybe of different nature to bring a variety of expertise from different sectors and types of institution to address high technological complexity and uncertainty. Finally, product diversification – the number of applications of the captured CO_2 - is always insignificant when entered as a linear term while environmental policy stringency, measured at the start of the project, is significant and positively signed, suggesting that tighter regulation incentivizes projects to climb the TRL scale.

In Column (2), we start testing non-linear effects. When we interact the number of partners with vertical integration, we find that full-chain projects with a larger number of partner are associated with a higher final TRL. It is therefore possible that in projects with many partners, vertical integration can act as an effective coordination mechanism, mitigating managerial complexity and reducing free-riding and opportunism (Grossman and Hart, 1986). In contrast, the interaction between product diversification and the number of partners is negatively correlated with the final TRL, suggesting that the combination of many partners and many partners leads to a complexity that is difficult to manage. Finally, in Column (4) we decompose the effect of environmental policy using different policy instruments and find that only the taxation on CO_2 emissions is significant. However, the test of joint significance of all policy measures tells us that altogether they all positively affect the final TRL.

In Columns (6) - (8), we analyze what affects the technological advancement of the project and use change in TRL (*trl_adv*) over the project duration. We control for the initial level of TRL (*trl_start*) and find that, as expected, it is negatively and significantly correlated with its change, as projects that start at a higher TRL level are closer to the commercial/operational phase and realize a lower delta. Our results also show that projects with a larger budget tend to achieve a more significant advance in the TRL. This result is important for its policy implications, as it shows that greater resources are significantly associated with greater capacity for technological advancement, in line with other evidence of the importance of financial support, especially in the technological scale-up phases (see, for example, Nemet et al., 2018).

When we focus on the organizational characteristics, we find that vertical integration is always positive and significant, suggesting that full-chain projects are more likely to climb up the TRL scale and get closer to market exploitation. As found by Yao et al. (2018), an integrated structure favour the alignment of objectives and the reduction of transaction costs, especially in the early stages of development. The number of partners (partner_count) appears now to have a positive effect on technological advancement, though only when the output is undiversified, i.e., specialized CO_2 utilization, as the coefficient on the interaction with the number of products is negative. A larger partnership therefore leads to greater technological advancement, but only in specialized projects. Interestingly the descriptive statistics in Table 5 show that larger partnerships tend form within projects with lower TRL, hence in the research and demonstration phase (trl_class = 1 and 2), suggesting that they need a higher number of partners who bring different expertise and know-how within the project in order to obtain a greater technological advancement.

TRL_class	Mean	N
1	9.45	29
2	11	122
3	4.05	41
Total	9.28	192

Table 5: Summary statistics for variable: *partner_count*, sorted by categories of: *trl_class*

We derive similar indications when observing the effect of diversification (*product_category_count*), which enters with a positive coefficient, and its interplay with project numerosity, which is negatively signed. Projects with diversified uses on captured carbon dioxide can achieve greater technical advancement but not within large consortia. Using the coefficients of the model (8) we find that the marginal effect of diversification cancels out at partnerships of 9 members.

Turning to environmental policy, we find that stringency is positively correlated with TRL growth in Col. (6), but the effect is no longer significant when we account for project location and CO_2 uses fixed effects in Col. (7). In Column (8), we focus on specific policy measures and find that public R&D expenditures (*avg_lc_rd_expenditures*) appear to significantly drive technological progress. Although the individual coefficients of the other policy instruments are insignificant, the F-test at the bottom of the table indicates that altogether they play a statistically significant effect on technical progress.

4.2 What drives the success of CCU projects?

To investigate what organizational, technological and policy characteristics can be associated with the project ability to achieve its goal and/or become operational, we perform a survival analysis. We use an Accelerated Failure Time (AFT) parametric model[13], which allows us to estimate how each factor contributes to accelerate or delay the time to failure, or success, as in our study. We rely on survival analysis instead of a logit (or probit model) because limited dependent variable models do not allow to account for the evolution over time of the risk of failure/success, nor to evaluate if and how the impact of the explanatory variables may change with duration of the project. In other words, we prefer to release the assumption that the "risk" of success is constant over time and, also, that the effects of the regressors do not change over time. In this framework, a positive coefficient indicates a longer time to reach success, and viceversa.

The multiplicative expression of the AFT model in its logarithmic form is the following:

$$log(T_i) = \beta_0 + \beta_1 \cdot X_{i,1} + \beta_2 \cdot x_{i,2} + ... + \beta_n \cdot X_{i,n} + \epsilon_i \tag{1}$$

Where T is the survival time to become successful – in our case, the time employed to carry out the project before it becomes operational or achieves its final objective. The coefficients of the covariates X describe the effect of each variable on the logarithm of time up to the project's "success"[14]. The error term can follow different distributional forms – exponential, lognormal, loglogistic, Weibull, Gompertz, generalized gamma – and the distributional form of the error term determines the regression model, affecting the interpretation of the results. To select the distributional form, we use the AIC, the Akaike Information

[13] A parametric model has more statistical power with respect to a non-parametric or semi-parametric (as the Cox Regression) that has, nevertheless, more robustness. Fonte?

[14] We use the logarithm so that we have an unconstrained dependent variable. See Saikia and Barman, 2017 for a review on AFT models.

Table 6: What factors affect technological maturity and progress (advancement) of CCU projects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	trl_end	*trl_end*	*trl_end*	*trl_end*	*trl_end*	*trl_adv*	*trl_adv*	*trl_adv*
trl_start						-0.296***	-0.300***	-0.302***
						(0.0376)	(0.0377)	(0.0373)
log_budget	0.404***	0.417***	0.411***	0.423***	0.354***	0.117**	0.0759*	0.0986**
	(0.0638)	(0.0656)	(0.0665)	(0.0679)	(0.0585)	(0.0461)	(0.0404)	(0.0399)
public_share	-1.005***	-1.031***	-1.060***	-0.843**	-0.935***	0.137	-0.261	0.106
	(0.338)	(0.345)	(0.343)	(0.337)	(0.331)	(0.224)	(0.247)	(0.234)
long_project	0.238	0.228	0.249	0.183	0.276	0.136	0.221*	0.0760
	(0.171)	(0.172)	(0.173)	(0.176)	(0.173)	(0.122)	(0.123)	(0.129)
vertical_integration	0.820***	0.227	0.301	0.345	0.182	0.330**	0.402**	0.390***
	(0.211)	(0.404)	(0.405)	(0.388)	(0.380)	(0.148)	(0.161)	(0.130)
partner_count	-0.0227	-0.0703**	-0.00693	-0.00383	0.0155	0.00795	0.0965***	0.0514**
	(0.0168)	(0.0309)	(0.0472)	(0.0470)	(0.0418)	(0.0117)	(0.0283)	(0.0254)
product_category_count	-0.120	-0.107	0.294	0.337	0.602**	-0.0565	0.597***	0.312*
	(0.167)	(0.167)	(0.303)	(0.336)	(0.259)	(0.0915)	(0.209)	(0.179)
vi_pc		0.0637*	0.0549*	0.0557*	0.0708**			
		(0.0331)	(0.0314)	(0.0304)	(0.0287)			
pcc_partnercount			-0.0441*	-0.0467	-0.0713***		-0.055**	-0.0355*
			(0.0265)	(0.0290)	(0.0231)		(0.0213)	(0.0188)
eps_start	0.260*	0.244*	0.207			0.150*	0.0454	
	(0.133)	(0.133)	(0.136)			(0.0769)	(0.0771)	
eps_delta_project	0.189	0.167	0.144			0.106	0.239	
	(0.386)	(0.395)	(0.400)			(0.286)	(0.241)	
avg_co2_trading_scheme				-0.0705				-0.0150
				(0.138)				(0.0636)
avg_co2_tax				0.0779*				-0.0446
				(0.0453)				(0.0293)
avg_lc_rd_expenditures				0.0646				0.157***
				(0.0696)				(0.0378)
avg_ets_prices				-0.00340	-0.00567			-0.00362
				(0.00443)	(0.00360)			(0.00279)
avg_pol					0.180***			
					(0.0623)			
Region FE	Yes	Yes	Yes	Yes	Yes	No	Yes	No
Product Category FE	Yes	Yes	Yes	Yes	Yes	No	Yes	No
Observations	192	192	192	191	192	101	101	101
R^2	0.527	0.538	0.543	0.556	0.570	0.478	0.607	0.553
F-test (p-value)								
H0: N.America = 0 & N. Europe = 0 & Others = 0 & S. Europe = 0	0.421	0.471	0.364	0.627	0.043		0.002	
H0: chemicals = 0 & co2 captured = 0 & building materials = 0 & others = 0	0.109	0.041	0.095	0.054	0.036		0.002	
H0: vertical_integration = 0 & vi_pc = 0		0.000	0.000	0.000	0.000			
H0: partner_count = 0 & vi_pc = 0		0.078	0.136	0.135	0.010			
H0: product_category_count = 0 & pcc_partnercount = 0			0.185	0.189	0.009		0.018	0.171
H0: partner_count = 0 & pcc_partnercount = 0			0.018	0.023	0.000		0.002	0.131
H0: avg_co2_trading_scheme = 0 & avg_co2_tax = 0 & avg_lc_rd_expenditures = 0 & avg_ets_prices = 0				0.031				0.001

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Criteria[15].

In Table 7 we present the maximum likelihood estimates of the AFT regression model.

Table 7: Survival Analysis – The time to success (AFT Weibull regressions)

	(1) _t	(2) _t	(3) _t	(4) _t
log_budget	0.0721***	0.0258	0.0777***	0.0268
	(0.0162)	(0.0203)	(0.0153)	(0.0210)
public_share	0.0483	-0.137	0.0270	-0.137
	(0.0805)	(0.120)	(0.0754)	(0.120)
long_project	0.321***	0.438***	0.300***	0.412***
	(0.0385)	(0.0561)	(0.0389)	(0.0576)
vertical_integration	0.0707*	0.0867*	0.212**	0.296***
	(0.0392)	(0.0480)	(0.0867)	(0.111)
partner_count	-0.00443	-0.00844**	0.0142	-0.00314
	(0.00383)	(0.00416)	(0.00965)	(0.00990)
product_category_count	0.0206	0.00595	0.240***	0.150
	(0.0401)	(0.0440)	(0.0888)	(0.100)
vi_pcc			-0.123*	-0.168**
			(0.0659)	(0.0813)
pcc_partnercount			-0.0142**	-0.00400
			(0.00600)	(0.00638)
avg_pol	0.0148		0.00709	
	(0.0123)		(0.0123)	
avg_co2_tax		0.0210		0.0174
		(0.0158)		(0.0161)
avg_lc_rd_expenditures		-0.0425*		-0.0412
		(0.0253)		(0.0254)
avg_co2_trading_scheme		0.138***		0.138***
		(0.0306)		(0.0307)
2.trl_class	-0.0821*	-0.143*	-0.0859*	-0.141*
	(0.0474)	(0.0797)	(0.0448)	(0.0771)
3.trl_class	-0.0644	0.0374	-0.0680	0.0668
	(0.0761)	(0.159)	(0.0717)	(0.166)
2.region_n	0.0182	0.366*	0.0627	0.363*
	(0.130)	(0.198)	(0.143)	(0.197)
3.region_n	0.200	0.224*	0.240*	0.223
	(0.122)	(0.134)	(0.131)	(0.139)
4.region_n	0.818***	0.917***	0.883***	0.928***
	(0.269)	(0.353)	(0.267)	(0.356)
5.region_n	0.236*	0.263*	0.266**	0.267*
	(0.123)	(0.139)	(0.129)	(0.141)
Constant	0.125	0.870**	-0.236	0.677
	(0.290)	(0.374)	(0.312)	(0.427)
ln_p	1.859***	1.540***	1.887***	1.543***
	(0.133)	(0.0999)	(0.141)	(0.103)
Log pseudolikelihood				-50.164
Wald chi2 (p-value)				0.000
Observations	192	192	192	192

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Across every specification, project budget (*log_budget*) has a positive coefficient (statistically significant in Columns (1) and (3)), implying that larger projects require more time to reach completion, consistent with the high complexity and capital intensity typical of large-scale ventures. Larger financial commitments are often associated with higher final

[15] In the Appendix Table 14, we report the estimation results when using different distributional forms for the error term and compare the associated AIC values. Based on results, we select the Weibull distribution.

TRL (as shown in Table see the results in subsection 4.1), and therefore may imply more coordination and engineering challenges, and heavier regulatory burden that seemingly slow down the path to operational maturity. In a similar fashion, also the coefficients on the binary variable *long_project* is positive and significant, confirming the difficulty of compressing the development cycles in such complex technological domains. Our control for technological progress, TRL, shows that projects at intermediate stages of technological maturity (class 2 covers TRL levels from 5 to 7) appear to achieve success more quickly compared to projects at early stages of the research activity (the default), suggesting that demonstration-phase projects benefit from prior learning and more settled research teams.

Turning to the organizational structure, vertical integration (*vertical_integration*) is positively and significantly associated with the time to success, which means that projects covering both capture and utilization - take longer to meet success. However, when we introduce the interaction with product diversification (*product category count*, which also enters with positive sign) in Column (3), we find that the overall effect is weakened, as product diversification appears to reduce the time to completion of vertically integrated projects. This nuanced result indicates that, ceteris paribus, vertically integrated projects are generally more complex and thus take longer to complete, but when the captured CO_2 is employed in diverse uses, the probability of success increases. possibly because this combination allows for economies of scope to be exploited. In terms of policy implications, this result suggests that integrated CCU projects are more viable and efficient in that they not reduce the potential problems of CO_2 supply but also allow the exploitation of economies of scope and more commercial uses.

In Column (3) we also find that product diversification may slow down the time to success, but not when the project has many partners as the interaction (*pcc_partnercount*) enters with a negative sign. To the extent that more CO_2 uses imply more partners with different specializations our variables of organizational structure seem to provide a coherent picture.

From the analysis of policy variables, two findings stand out. First, the negative coefficient on public R&D expenditures (*avg_lc_rd_expenditures*) in Column (2) suggests that when the public support for low-carbon R&D projects tend to succeed more quickly, possibly because such policies help mitigate early-stage uncertainty and financing bottlenecks. Second, the positive and significant coefficient on CO_2 trading schemes (*avg_co2_trading_scheme*) in both Columns (2) and (4) indicates that more established trading systems appear to delay project success, an outcome which suggests that trading schemes may "substitute" CCU projects in that they allow an economic alternative to "brown" corporations. Overall, our evidence from the analysis of policy instruments suggests that a careful balance between the benefits and the costs, also in terms of incentives, related to the functioning on each measure is crucial.

Finally, regional dummies reveal that projects located in Northern and Southern Europe have significantly longer completion times compared to Asia (the default) while those in North American projects are quicker to reach completion or to become operations.

5 Conclusion. To be written

References

Abdulla, A., Hanna, R., Schell, K. R., Babacan, O., & Victor, D. G. (2020). Explaining successful and failed investments in us carbon capture and storage using empirical and expert assessments. *Environmental Research Letters*, *16*(1), 014036.

Agency, I. E. (n.d.). World Energy Outlook 2019 IEA website. https://www.iea.org/reports/world-energy-outlook-2019

Arning, K., Offermann-van Heek, J., Linzenich, A., Kätelhön, A., Sternberg, A., Bardow, A., & Ziefle, M. (2019). Same or different? insights on public perception and acceptance of carbon capture and storage or utilization in germany. *Energy policy*, *125*, 235–249.

Barchi, A., Illich, M., Rondi, L., et al. (2024). Green transition and decarbonization projects: Are we doing enough?

Bruhn, T., Naims, H., & Olfe-Kräutlein, B. (2016). Separating the debate on co2 utilisation from carbon capture and storage. *Environmental Science & Policy*, *60*, 38–43.

Choi, J., & Contractor, F. J. (2019). Improving the progress of research & development (r&d) projects by selecting an optimal alliance structure and partner type. *British Journal of Management*, *30*(4), 791–809.

Colombe, C., Leibowicz, B. D., & Mendoza, B. R. (2024). The effects of policy uncertainty and risk aversion on carbon capture, utilization, and storage investments. *Energy Policy*, *192*, 114212.

Fan, J.-L., Xu, M., Yang, L., Zhang, X., & Li, F. (2019). How can carbon capture utilization and storage be incentivized in china? a perspective based on the 45q tax credit provisions. *Energy Policy*, *132*, 1229–1240.

Foray, D., & Steinmueller, E. (2003). On the economics of r&d and technological collaborations: Insights and results from the project colline. *Economics of Innovation and New Technology*, *12*(1), 77–91.

Grossman, S. J., & Hart, O. D. (1986). The costs and benefits of ownership: A theory of vertical and lateral integration. *Journal of political economy*, *94*(4), 691–719.

Hepburn, C., Adlen, E., Beddington, J., Carter, E. A., Fuss, S., Mac Dowell, N., Minx, J. C., Smith, P., & Williams, C. K. (2019). The technological and economic prospects for co_2 utilization and removal. *Nature*, *575*(7781), 87–97.

Hottenrott, H., & Lopes-Bento, C. (2016). R&d partnerships and innovation performance: Can there be too much of a good thing? *Journal of Product Innovation Management*, *33*(6), 773–794.

IEA, I. E. A. (2019, May). *Transforming industry through CCUS* (tech. rep.). https://iea.blob.core.windows.net/assets/0d0b4984-f391-44f9-854f-fda1ebf8d8df/Transforming_Industry_through_CCUS.pdf

ITUL, A., DIAZ, R. A., EULAERTS, O. D., GEORGAKAKI, A., GRABOWSKA, M., KAPETAKI, Z., INCE, E., LETOUT, S., KUOKKANEN, A., MOUNTRAKI, A., et al. (2023). Clean energy technology observatory: Carbon capture storage and utilisation in the european union-2023 status report on technology development, trends, value chains and markets.

Jevons, W. S. (1865). The coal question: Can britain survive. *First published in*, *165*.

Klein, B., Crawford, R. G., & Alchian, A. A. (1978). Vertical integration, appropriable rents, and the competitive contracting process. *The journal of Law and Economics*, *21*(2), 297–326.

Koelle, B., Scodanibbio, L., Vincent, K., Harvey, B., van Aalst, M., Rigg, S., Ward, N., & Curl, M. (2019). A guide to effective collaboration and learning in consortia. *London: Red Cross Red Crescent Climate Centre.[Google Scholar]*.

Kruse, T., Dechezleprêtre, A., Saffar, R., & Robert, L. (2022). Measuring environmental policy stringency in oecd countries: An update of the oecd composite eps indicator. *OECD Economic Department Working Papers*, (1703), 0_1–56.

Lupion, M., & Herzog, H. J. (2013). Ner300: Lessons learnt in attempting to secure ccs projects in europe. *International Journal of Greenhouse Gas Control*, *19*, 19–25.

Mac Dowell, N., Fennell, P. S., Shah, N., & Maitland, G. C. (2017). The role of co_2 capture and utilization in mitigating climate change. *Nature climate change*, *7*(4), 243–249.

Martin-Roberts, E., Scott, V., Flude, S., Johnson, G., Haszeldine, R. S., & Gilfillan, S. (2021). Carbon capture and storage at the end of a lost decade. *One Earth*, *4*(11), 1569–1584.

Memon, S. U. R., Manzoor, R., Fatima, A., Javed, F., Zainab, A., Ali, L., Ullah, U., Saleem, A., & Ullah, Q. (2024). A comprehensive review of carbon capture, utilization, and storage (ccus): Technological advances, environmental impact, and economic feasibility. *Sch Acad J Biosci*, *7*, 184–204.

Mowery, D. C., & Rosenberg, N. (1991). *Technology and the pursuit of economic growth*. Cambridge University Press.

Nath, F., Mahmood, M. N., & Yousuf, N. (2024). Recent advances in ccus: A critical review on technologies, regulatory aspects and economics. *Geoenergy Science and Engineering*, *238*, 212726.

Nawaz, M., Suleman, H., & Maulud, A. S. (2022). Carbon capture and utilization: A bibliometric analysis from 2007–2021. *Energies*, *15*(18), 6611.

Nemet, G. F., Callaghan, M. W., Creutzig, F., Fuss, S., Hartmann, J., Hilaire, J., Lamb, W. F., Minx, J. C., Rogers, S., & Smith, P. (2018). Negative emissions—part 3: Innovation and upscaling. *Environmental Research Letters*, *13*(6), 063003.

Reyes-Lúa, A., & Jordal, K. (2020). Industrial co_2 capture projects: Lessons learned and needs for progressing towards full-scale implementation. *Changes*, *1*, 10.

Saikia, R., & Barman, M. P. (2017). A review on accelerated failure time models. *International Journal of Statistics and Systems*, *12*(2), 311–322.

Song, X., Ge, Z., Zhang, W., Wang, Z., Huang, Y., & Liu, H. (2023). Study on multi-subject behavior game of ccus cooperative alliance. *Energy*, *262*, 125229.

Wang, N., Akimoto, K., & Nemet, G. F. (2021). What went wrong? learning from three decades of carbon capture, utilization and sequestration (ccus) pilot and demonstration projects. *Energy Policy*, *158*, 112546.

Yao, X., Zhong, P., Zhang, X., & Zhu, L. (2018). Business model design for the carbon capture utilization and storage (ccus) project in china. *Energy policy*, *121*, 519–533.

Zhang, J., Liu, Y., Yang, L., Zhang, J., & Li, X. (2025). An assessment of the effectiveness of ccs technology incentive policies based on dynamic cge model. *Energy Policy*, *198*, 114468.

Appendices

A Data

A.1 Description of the sources and the variables in the full sample

Dataset	Organization	Focus	Selected Projects	Geographic Focus	Last Update	Source
CO_2 Value Europe CCU Database	CO_2 Value Europe	CCU research projects (TRL 3-7)	278	Primarily Europe	2023	[1]
IEA Industrial CCUS Project Database	IEA	Industrial CCU projects (TRL ¿ 7)	22	Global	March 2023	[2]
IEA Demonstration Projects Database	IEA	Demonstration projects for clean energy technologies (TRL 5-7)	20	Global	Continuously Updated	[3]
DAC Coalition's Global DAC Deployments Database	DAC Coalition	Demonstration and industrial DAC projects (TRL ¿ 5/6)	32	Global	Continuously updated	[4]
Additional Non-Catalogued Projects	NA	Industrial CCU projects (TRL ¿ 8)	7	Global	December 2024	Manual

Table 8: Databases and sources

Variable	**Description**
Project Name	Name of the project.
Project Lead	Name of the project leader or leading organization.
Location	Localization information including region, country, and city/town.
Start Date – End Date	Project's start and end dates.
Project Status	Current status of the project (e.g., Ongoing, Upcoming, Completed).
Facility Stage	Stage of the facility (e.g., Planned, Under Construction, Operational, Completed).
Project Budget	Total project budget (private + public funding).
% (Public Investment)	Percentage of public investment in the total project budget.
Institution	Public institution that funded the project.
CO_2 Source	Source of CO_2 utilized in the project (e.g., Atmospheric CO_2, Industrial flue gasses).
CCU Technology Category	CCU technology category (e.g., Capture, CCU, DACC).
Start TRL – End TRL	Technology readiness levels at the start and end of the project.
CO_2 Capture/Utilization [t/y]	Amount of CO_2 captured/utilized in one year by the project.
Production Volume [t/y]	Amount of product realized in one year. If multiple products are listed, this is an average per product.
Specific Product	Specific products created by the project (up to 4 entries per project).
Info on Utilization	Details on CO_2 utilization methods (e.g., Catalytic, Thermal conversion).
Product Category	Category of the product realized by the project (up to 4 entries).
Partner	Names of project partners (up to 46 entries per project).

Table 9: Variables in the dataset and definitions

Var	Mean	SD	Min	p25	p50	p75	Max	N
success	0.409	0.492	0.00	0.00	0.00	1.00	1.00	359
duration	4.222	2.428	1.00	3.00	4.00	5.00	16.00	351
trl_start	5.886	2.019	1.00	4.00	6.00	7.00	9.00	158
trl_end	6.615	1.613	3.00	6.00	7.00	8.00	9.00	314
trl_adv	1.082	0.731	0.00	1.00	1.00	2.00	3.00	158
trl_class	2.185	0.633	1.00	2.00	2.00	3.00	3.00	314
budget	1.493e+08	8.883e+08	71429	3000000	49651810	15000000	1.16e+10	268
public_share	0.660	0.332	0.00	0.45	0.76	0.92	1.00	233
partner_count	7.561	6.243	1.00	3.00	6.00	11.0	45.00	344
vertical_integration	0.649	0.478	0.00	0.00	1.00	1.00	1.00	359
product_category_count	1.284	0.499	1.00	1.00	1.00	2.00	3.00	359
long_project	0.325	0.469	0.00	0.00	0.00	1.00	1.00	351

Table 10: Summary Statistics: CCU projects - Full sample

Project class	Number of CCU projects
1 Product Category	264
2 Product Categories	87
3 Product Categories	8
Total	359

Table 11: Number of CCU projects by associated product category count - Full sample

Product Category	%	Number of CCU projects
e-Fuels	32%	146
Chemicals	22%	100
Captured CO_2	16%	72
Building materials	8%	36
Biofuels	5%	25
Polymers	3%	16
Biochemicals	3%	16
Governance & cluster development activities	3%	14
Food/Feed	3%	12
Fertilizers	2%	10
Power and heat	2%	9
Consumer goods	1%	3
Fuels	1%	3
Total	100%	462

Table 12: Number of CCU projects by product category - Full sample. Each project can feature in more than one product category.

A.2 CO_2 origin and projects geographical distribution

The dataset is geographically polarized towards the EU, partly due to better coverage of coverage, which, in turn, may be due to a greater sensibility towards environmental problems. (Figure 4).

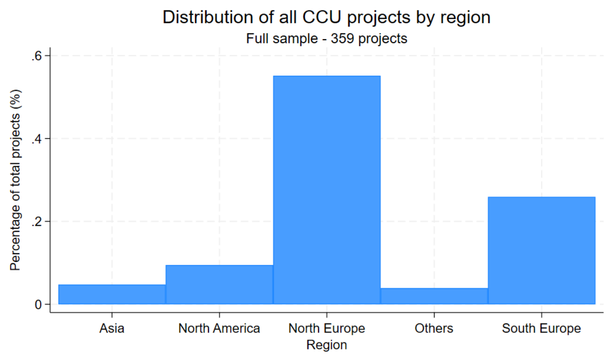

Figure 4: Projects share by Region

Table 13 shows the Top 15 countries by *facility stage*. Germany tops the list, the UK and China have the highest share of completed projects and the US of operational ones.

Country	Completed	Planned	Under Construction	Operational	Total Projects
Germany	35,2%	37,0%	11,1%	16,7%	54
Spain	25,0%	56,3%	15,6%	3,1%	32
France	39,1%	43,5%	4,3%	13,0%	23
United States	15,0%	40,0%	15,0%	30,0%	20
Netherlands	42,1%	26,3%	10,5%	21,1%	19
Belgium	33,3%	44,4%	16,7%	5,6%	18
Norway	13,3%	33,3%	40,0%	13,3%	15
United Kingdom	61,5%	23,1%	15,4%	0,0%	13
Canada	30,8%	23,1%	30,8%	15,4%	13
Italy	25,0%	58,3%	8,3%	8,3%	12
Denmark	18,2%	45,5%	18,2%	18,2%	11
Sweden	10,0%	70,0%	20,0%	0,0%	10
China	55,6%	11,1%	33,3%	0,0%	9
Greece	12,5%	75,0%	12,5%	0,0%	8
Finland	25,0%	62,5%	0,0%	12,5%	8

Table 13: Top 15 Countries per Number of CCU Projects

B Empirical design - Selection of error distribution

	(1) Weibull	(2) Exponential	(3) LogLogistic	(4) Lognormal	(5) Generalized Gamma
analysis time when record ends					
log_budget	0.0721***	0.208***	0.0563**	0.0661**	0.0810***
	(0.0162)	(0.0697)	(0.0259)	(0.0260)	(0.0150)
public_share	0.0483	0.442	0.0363	0.123	0.0246
	(0.0805)	(0.331)	(0.0841)	(0.108)	(0.0784)
long_project	0.321***	0.0115	0.314***	0.364***	0.310***
	(0.0385)	(0.172)	(0.0396)	(0.0504)	(0.0459)
vertical_integration	0.0707*	0.402**	0.0681*	0.112*	0.0712*
	(0.0392)	(0.180)	(0.0411)	(0.0634)	(0.0406)
partner_count	-0.00443	-0.0227	-0.00262	-0.00300	-0.00534
	(0.00383)	(0.0150)	(0.00325)	(0.00415)	(0.00469)
product_category_count	0.0206	0.215	0.0265	0.0368	0.0206
	(0.0401)	(0.190)	(0.0380)	(0.0504)	(0.0406)
trl_class=1	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
trl_class=2	-0.0821*	-0.593**	-0.101**	-0.175**	-0.0527
	(0.0474)	(0.233)	(0.0483)	(0.0748)	(0.0502)
trl_class=3	-0.0644	-0.415	-0.0568	-0.135	-0.0568
	(0.0761)	(0.376)	(0.0876)	(0.114)	(0.0608)
avg_pol	0.0148	0.0808	0.0124	0.0201	0.0149
	(0.0123)	(0.0628)	(0.0132)	(0.0232)	(0.0118)
Asia	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
North America	0.0182	0.426	0.125	0.173	-0.0375
	(0.130)	(0.544)	(0.163)	(0.192)	(0.125)
North Europe	0.200	0.687	0.290*	0.314	0.166
	(0.122)	(0.475)	(0.164)	(0.199)	(0.102)
Others	0.818***	1.041	0.447	0.473	0.809***
	(0.269)	-1.271	-6.906	(0.493)	(0.206)
South Europe	0.236*	0.898*	0.328*	0.342	0.202**
	(0.123)	(0.504)	(0.168)	(0.212)	(0.100)
Constant	0.125	-2.027	0.236	0.0174	0.0527
	(0.290)	-1.285	(0.464)	(0.537)	(0.242)
/					
ln_p	1.859***				
	(0.133)				
lngamma			-2.069***		
			(0.163)		
lnsigma				-1.253***	-2.134***
				(0.158)	(0.190)
kappa					1.602***
					(0.436)
Observations	192	192	192	192	192
Log likelihood	-39,791	-144,728	-43,138	-56,749	-37,890
AIC	109,582	317,456	116,276	143,497	107,781

Table 14: Selection of best fitting distribution with AIC