# Proposal:
# The Economics of Clean Energy Demonstration Projects

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## 1 Introduction

Effective climate mitigation requires addressing not only the carbon externality but the broader set of market failures that distort the development and adoption of clean technologies (Gillingham and Stock, 2018; Armitage et al., 2023). The standard two-instrument view pairs carbon pricing with support for innovation (Acemoglu et al., 2012). We highlight a distinct and underappreciated margin: an *information externality* from first-of-a-kind (FOAK) projects (Armitage et al., 2023). Tacit knowledge plays an important role in large scale projects. Even with detailed engineering designs, the realized cost of using a technology at scale in the real world is uncertain until the first investment has taken place. Because the first mover does not internalize the value that its information creates for others, private investment is below the social optimum. This channel is conceptually different from R&D spillovers (which expand the knowledge frontier) and from learning-by-doing (which lowers costs with cumulative output). Here, the welfare gain is information revelation rather than cost reduction per se.

Drawing on insights from the engineering community, this information externality is already shaping policy. Recent U.S. programs—most prominently the Department of Energy's demonstration "hubs" for clean hydrogen and direct air capture (DAC)—explicitly

subsidized first-of-a-kind (FOAK) project to take provide information to other potential entrants and increase total investment in clean energy technologies. While engineers emphasized FOAK/second-of-a-kind (SOAK) considerations, economics offered little structure for determining the correct *size* of these demonstration or even providing guidance on the factors that should affect the subsidy size.

In this paper, we develop a tractable model of information externalities in sequential investment decisions and apply it to direct air capture. [Insert description of model once finalized]. The goal is a compact framework that policymakers can use to size demonstration subsidies and to integrate information externalities with standard carbon pricing and innovation policy.

## 2 Related Literature

**Information externalities and strategic experimentation.** Our work contributes to the literature on information externalities in sequential investment and strategic experimentation, where early actions generate signals that later agents can free-ride on, leading to under-experimentation and inefficient timing relative to the social optimum (e.g., (Hendricks and Kovenock, 1989; Rob, 1991; Chamley and Gale, 1994; Doyle, 2010).[1] Our contribution is to tie the insights from this literature to the case of clean energy technologies in a transparent model and use that model to calibrate optimal subsidies for direct air capture. In doing so, we also contribute to this literature by studying the interaction of the information externalities with other environmental externalities.

**Information externalities in climate economics.** Our work also contributes to the literature on climate innovation. Ths literature mostly focuses on externalities related to innovation(e.g., Acemoglu et al., 2012, 2016; Hart, 2019) or learning-by-doing (e.g., Nemet, 2006; Arkolakis and Walsh, 2023). In an excellent review article, Armitage et al. (2023)

[1] See also, Bolton and Harris (1999); Keller et al. (2005); Décamps and Mariotti (2004); Hausmann and Rodrik (2003).

highlight additional relevant externalities, including the information externalities motivating subsidies for demonstration projects. We contribute to this literature by studying this externality in a micro-founded, sequential learning model.

**Policy design and implementation for demonstrations.** Our work also contributes to policy thinking on demonstration programs that seeks to harness spillovers from publicly supported first-of-a-kind projects (e.g., Bergman (2023); National Academies of Sciences, Engineering, and Medicine (2019); International Energy Agency (2024); Lester and Hart (2015)). We complement this existing work by providing a theoretical framework that can be used to determine the optimal subsidy for demonstration projects and the forces that determine this optimal subsidy. We also design an auction mechanism that can help reveal the information needed for this subsidy.

**Direct air capture (DAC).** Our work also contributes to the academic literature on DAC, which documents high current costs, wide uncertainty, and the importance of policy-driven learning-by-doing and deployment (e.g., Realmonte et al. (2019); Keith et al. (2018); Sanz-Pérez et al. (2016); Gambhir and Tavoni (2019); Shayegh et al. (2021)). We contribute a formal adoption model in which FOAK DAC projects reveal cost information for followers. We derive the optimal, per-project FOAK bonus (and its $N$-firm generalization) and provide survey and auction designs to recover the primitives required to calibrate these transfers for DAC demonstration policy.

# 3 Simple Model

In this section, we analyze a simple two-firm model of direct air capture to highlight the relevant intuition. Intuitively, we think about two firm who, if they undertake an investment, will the same technology and scientific knowledge to undertake a DAC project.

Even conditional on using the same technology, the relative success of two projects depends on a many smaller decisions made during the construction phase and during ongoing

operations. These decision rely on tacit knowledge that cannot be perfectly codified. This has two important implications. First, even thought the technology is common across firms, the exact cost of actually using the technology at scale in a real-world environment is subject to uncertainty. Second, even when firms use the same technology, their costs are unlikely to be identical.

The core of our model is an *information externality*, the first firm to invest reduces uncertainty for the second firm, because it provides information on the effectiveness of the common technology. We study how this information externality interacts with negative externality from carbon emissions. We also study how government policy can address the information externality through optimal policy when all other externalities are addressed through separate policies or through constrained-efficiency policy that account for interacting market failures.

## 3.1 Primitives and timing

- **Policy and scale.** A plant that invests captures a fixed quantity $Q > 0$ of $CO_2$. The per-ton policy support is $s$. Deterministic project revenue is $P \equiv sQ$.
- **Random cost.** If firm $i \in \{A, B\}$ invests, it pays a random *total* cost $C_i$.
- **Preferences.** Each firm has $u(w) = -\exp(-\rho w)$ where $w$ is wealth.
- **Timeline.** (i) Firm A decides whether to invest. If it does, its realized cost $c_A$ becomes public. (ii) Firm B then decides, taking into account $c_A$.
- **Policy.** Firm A receives a subsidy $\tau \geq 0$ if and only if it invests.

## 3.2 Beliefs and Information

Firm $i \in \{A, B\}$ has realized total cost

$$C_i \;=\; \theta + \epsilon_i,$$

the sum of a common technology component and an idiosyncratic component. The common part reflects sector-level unknowns that persist because the technology has not yet been implemented at commercial scale:

$$\theta \sim \mathcal{N}(\mu_0, \tau_0^2).$$

Conditional on $\theta$, each firm draws an idiosyncratic shock

$$\epsilon_i \sim \mathcal{N}(0, v),$$

with $(\epsilon_i)_i$ i.i.d. across firms and independent of $\theta$. This is only observed after the firm decides to invest.

If $\theta$ *were* known with certainty, then $C_i \mid \theta \sim \mathcal{N}(\theta, v)$. If no other firm has invested, the cost faced by a prospective investor is

$$C \sim \mathcal{N}(\mu_0, V_0), \qquad V_0 \equiv \tau_0^2 + v.$$

We call this the *Prior predictive cost*.

If (and only if) firm $A$ invests, its realized cost $c_A$ is perfectly observed by $B$ before $B$ decides whether to invest. Conjugate Normal updating then gives $B$'s posterior over the common component and its predictive cost:

$$\alpha_1 \;\equiv\; \frac{\tau_0^2}{\tau_0^2 + v}, \qquad \mu_1 \;=\; (1-\alpha_1)\mu_0 + \alpha_1\, c_A, \qquad \tau_1^2 \;=\; \frac{\tau_0^2\, v}{\tau_0^2 + v},$$

$$C_B \mid c_A \;\sim\; \mathcal{N}\big(\mu_1,\; V_1\big), \qquad V_1 \;\equiv\; v + \tau_1^2 \;=\; (1-\alpha_1^2)\, V_0 \;=\; v\,\frac{v + 2\tau_0^2}{\tau_0^2 + v}.$$

If $A$ does not invest, $B$ receives no signal and retains the prior $\mathcal{N}(\mu_0, V_0)$.

## 3.3 CARA–Normal certainty equivalents (CEs)

If a monetary payoff $X$ is Normally distributed, $X \sim \mathcal{N}(\mu, \sigma^2)$, then with CARA utility a decision maker is *exactly* indifferent between $X$ and a sure amount equal to the *certainty equivalent*

$$\mathrm{CE}(X) \;=\; \mu \;-\; \frac{\rho}{2}\,\sigma^2,$$

independent of wealth. Throughout, investment choices can therefore be expressed in dollars via CEs, and a sure transfer $\tau$ simply adds $\tau$ to the CE.

## 3.4 Firm A decision process

$A$'s invest payoff is $sQ - c_A + \tau$, with $C_A \sim \mathcal{N}(\mu_0, V_0)$. Hence

$$\mathrm{CE}_A^{(\mathrm{invest})} \;=\; (sQ - \mu_0) + \tau \;-\; \frac{\rho}{2} V_0 \quad \text{and} \quad \mathrm{CE}_A^{(\mathrm{not})} \;=\; 0.$$

Thus $A$ invests iff

$$\underbrace{\tau + sQ - c_A}_{\text{payoff from investing}} \;\geq\; \underbrace{\mu_0 + \frac{\rho}{2} V_0 m_0}_{\text{expected costs including risk premium}} \qquad . \tag{1}$$

## 3.5 Follower $B$ after observing $A$

If (and only if) $A$ invests, its realized cost $c_A$ is revealed. $B$ its predicted cost via Normal–Normal conjugacy:

$$C_B \mid c_A \;\sim\; \mathcal{N}\big(\mu_1,\, V_1\big) \tag{2}$$

With CARA–Normal, the certainty equivalent of investing for $B$ is

$$\mathrm{CE}_B^{(\mathrm{invest})}(c_A) \;=\; sQ - \mu_1 \;-\; \frac{\rho}{2}\, V_1.$$

Hence $B$ invests after seeing $c_A$ iff

$$sQ - \mu_1 \;\geq\; \frac{\rho}{2} V_1 \quad\Longleftrightarrow\quad (1-\alpha_1)\mu_0 + \alpha_1 c_A \;\leq\; sQ - \frac{\rho}{2} V_1. \tag{3}$$

Equivalently, there is a *cost threshold* for the revealed FOAK cost:

$$c_A \;\leq\; c_A^\star \;\equiv\; \mu_0 \;+\; \frac{sQ - \frac{\rho}{2} V_1 - \mu_0}{\alpha_1}. \tag{4}$$

If $A$ does *not* invest (no signal), $B$ retains the prior and invests iff

$$sQ - \mu_0 \;\geq\; \frac{\rho}{2} V_0. \tag{5}$$

**When does $B$'s decision change?** Let the *baseline* decision be the prior rule (5). When $A$ invests and reveals $c_A$:

- If the baseline is *invest* ($sQ - \mu_0 \geq \frac{\rho}{2} V_0$), then $B$ reverses to *not invest* iff $c_A > c_A^\star$.
- If the baseline is *not invest* ($sQ - \mu_0 < \frac{\rho}{2} V_0$), then $B$ switches to *invest* iff $c_A \leq c_A^\star$.

Because $A$'s invest decision does not depend on its realized $c_A$, we have $c_A \sim \mathcal{N}(\mu_0, V_0)$ conditional on $A$ investing. Thus the ex-ante probability that $B$ invests after observing $c_A$ is

$$p_1 \;=\; \Pr(c_A \leq c_A^\star) \;=\; \Phi\!\left(\frac{c_A^\star - \mu_0}{\sqrt{V_0}}\right) \;=\; \Phi\!\left(\frac{sQ - \frac{\rho}{2} V_1 - \mu_0}{\alpha_1 \sqrt{V_0}}\right),$$

and, correspondingly, the probability of a reversal from the baseline is

$$\Pr(\text{switch}) \;=\; \begin{cases} 1 - p_1, & \text{if } sQ - \mu_0 \geq \frac{\rho}{2} V_0 \quad \text{(baseline invest)}, \\ p_1, & \text{if } sQ - \mu_0 < \frac{\rho}{2} V_0 \quad \text{(baseline not invest)}. \end{cases}$$

## 3.6 Planner and the Optimal FOAK Payment

*Primitives used below:*

$$P = sQ, \qquad \delta \equiv (S-s)Q, \qquad \alpha_1 = \frac{\tau_0^2}{\tau_0^2 + v}, \qquad V_0 = \tau_0^2 + v, \qquad V_1 = v + \frac{\tau_0^2 v}{\tau_0^2 + v}.$$

If $A$ invests, its revealed cost $c_A$ implies $\mu_1 = (1-\alpha_1)\mu_0 + \alpha_1 c_A$ and, ex-ante over $c_A \sim \mathcal{N}(\mu_0, V_0)$,

$$p_0 \equiv \mathbf{1}\{\, sQ - \mu_0 \geq \tfrac{\rho}{2} V_0 \,\}, \qquad p_1 \equiv \Phi\left(\frac{sQ - \mu_0 - \frac{\rho}{2} V_1}{\alpha_1 \sqrt{V_0}}\right),$$

the follower's invest probability without and with the FOAK signal, respectively. We let $S$ be the social cost of carbon. A per-unit subsidy of $s = S$, implies that the carbon emissions externality is fully internalized and does not affect the optimal demonstration subsidy.

We consider a planner that ignores risk *per se* and maximizes expected resource surplus.[2] The FOAK is desirable iff

$$\underbrace{(sQ - \mu_0)}_{\text{leader's real surplus}} + \underbrace{\text{EVSI}_B^{\text{RO}}}_{\text{follower's expected incremental real surplus}} + \underbrace{\delta\,[\,1 + p_1 - p_0\,]}_{\text{climate mispricing top-up}} \geq 0, \tag{6}$$

where

$$\text{EVSI}_B^{\text{RO}} = (sQ - \mu_0)\,\Phi\left(\frac{sQ - \mu_0}{\alpha_1\sqrt{V_0}}\right) + \alpha_1\sqrt{V_0}\,\phi\left(\frac{sQ - \mu_0}{\alpha_1\sqrt{V_0}}\right) - (sQ - \mu_0)^+. \tag{7}$$

**Decentralization.** For what follows, we focus on the Pigouvian subsidy, i.e., the tax that fully internalizes the externality and makes the first firm's objective the same as the social planner's objective. Since this is a discrete model with corner solutions, the outcome is often the same for a wide range of taxes. We focus on the Pigouvian tax because this concept generalizes to models with continuous choice (e.g., models where firm can pick the quantity

[2]The results are similar with a more utilitarian social planner. In this case, however, the planner will pay a subsidy to the firms just to reduce their risk, independent of whether it changes their behavior. Policymakers are generally not supportive of such inframarginal transfers.

they want to produce). In general, the Pigouvian tax is not the minimum tax needed to influence behavior in this discrete model.

With CARA firms, $A$'s private threshold is $sQ - \mu_0 + \tau \geq \frac{\rho}{2} V_0$. The FOAK payment that implements (6) (i.e., fully internalizes the externality) is[3]

$$\tau^*_{\text{RO}}(s, S) = \underbrace{\text{EVSI}^{\text{RO}}_B}_{\text{internalize information externality}} + \underbrace{\frac{\rho}{2} V_0}_{\text{offset risk aversion}} + \underbrace{\delta \left[ 1 + p_1 - p_0 \right]}_{\text{address the climate externality}} . \tag{8}$$

### 3.7 Calibration Sketch

The following parameters are sufficient to calculate the Pigouvian subsidy.

**P1 Scale and policy:** $(Q,\ s,\ S)$, with per-project climate mispricing $\delta \equiv (S - s)Q$.

**P2 Prior predictive cost (project dollars):** $(\mu_0,\ V_0)$ for the FOAK's total cost. *How:* fit per-ton 10/50/90 DAC cost percentiles to a Normal and scale by $Q$. Shayegh et al. (2021) provide this information.

**P3 Signal informativeness:** $\alpha_1 \in (0, 1)$ (how much one realized cost moves followers' means). *How:* brief survey ("how much would one realized cost shift your expectation?") or elicit cross-project correlation $\rho$ and set $\alpha_1 = \rho$.

## 4 Full Model

- Generalize this to N firms.
- Make quantity endogenous? (if so, maybe change simply model)
- Re-do all results from above.

[3] If the social planner maximizes utility rather than real resources, it would not want to offset risk aversion. It would, however, pay the first firm to invest in order to reduce uncertainty for the second firm *even if the second firm would invest anyway.*

- Combine this with the survey to get the quantitative predictions.
- Develop an auction mechanism that would reveal all of the relevant information.

# References


Acemoglu, D., P. Aghion, L. Bursztyn, and D. Hemous (2012): "The environment and directed technical change," *American Economic Review*, 102, 131–166.

Acemoglu, D., U. Akcigit, D. Hanley, and W. Kerr (2016): "Transition to clean technology," *Journal of Political Economy*, 124, 52–104.

Arkolakis, C., and C. Walsh (2023): "Clean growth,"Technical report, National Bureau of Economic Research.

Armitage, S. C., N. Bakhtian, and A. B. Jaffe (2023): "Innovation Market Failures and the Design of New Climate Policy Instruments," NBER Working Paper 31622, National Bureau of Economic Research, 10.3386/w31622.

Bergman, A. (2023): "Decisionmaking for Demonstration Projects,"Technical Report Report 23-11, Resources for the Future, https://media.rff.org/documents/Report_23-11_Decisionmaking_for_Demonstration_Projects.pdf.

Bolton, P., and C. Harris (1999): "Strategic Experimentation," *Econometrica*, 67, 349–374, 10.1111/1468-0262.00022.

Chamley, C., and D. Gale (1994): "Information Revelation and Strategic Delay in a Model of Investment," *Econometrica*, 62, 1065–1085.

Décamps, J.-P., and T. Mariotti (2004): "Investment Timing and Learning Externalities," *Journal of Economic Theory*, 118, 80–102, 10.1016/j.jet.2003.11.006.

Doyle, M. (2010): "Informational externalities, strategic delay, and optimal investment subsidies," *Canadian Journal of Economics/Revue canadienne d'économique*, 43, 941–966.

Gambhir, A., and M. Tavoni (2019): "Direct Air Carbon Capture and Sequestration: How It Works and How It Could Contribute to Climate-Change Mitigation," *One Earth*, 1, 405–409, 10.1016/j.oneear.2019.11.006.

Gillingham, K., and J. H. Stock (2018): "The cost of reducing greenhouse gas emissions," *Journal of Economic Perspectives*, 32, 53–72.

Hart, R. (2019): "To everything there is a season: Carbon pricing, research subsidies, and the transition to fossil-free energy," *Journal of the Association of Environmental and Resource Economists*, 6, 349–389.

Hausmann, R., and D. Rodrik (2003): "Economic development as self-discovery," *Journal of Development Economics*, 72, 603–633, 10.1016/S0304-3878(03)00124-X.

Hendricks, K., and D. Kovenock (1989): "Asymmetric Information, Information Externalities, and Efficiency: The Case of Oil Exploration," *RAND Journal of Economics*, 20, 164–182.

International Energy Agency (2024): "Advancing Clean Energy Demonstration Projects,"Technical report, IEA, https://www.iea.org/reports/advancing-clean-energy-demonstration-projects.

Keith, D. W., G. Holmes, D. S. Angelo, and K. Heidel (2018): "A Process for Capturing CO_2 from the Atmosphere," *Joule*, 2, 1573–1594, 10.1016/j.joule.2018.05.006.

Keller, G., S. Rady, and M. W. Cripps (2005): "Strategic Experimentation with Exponential Bandits," *Econometrica*, 73, 39–68, 10.1111/j.1468-0262.2005.00564.x.

Lester, R. K., and D. M. Hart (2015): "Closing the Energy-Demonstration Gap," *Issues in Science and Technology*, 31, 48–54.

National Academies of Sciences, Engineering, and Medicine (2019): *Negative Emissions Technologies and Reliable Sequestration: A Research Agenda*, Washington, DC: The National Academies Press, 10.17226/25259.

Nemet, G. F. (2006): "Beyond the learning curve: Factors influencing cost reductions in photovoltaics," *Energy Policy*, 34, 3218–3232.

Realmonte, G., L. Drouet, A. Gambhir, J. Glynn, A. Hawkes, A. C. Köberle, and M. Tavoni (2019): "An inter-model assessment of the role of direct air capture in deep mitigation pathways," *Nature Communications*, 10, 3277, 10.1038/s41467-019-10842-5.

Rob, R. (1991): "Learning and Capacity Expansion under Demand Uncertainty," *Review of Economic Studies*, 58, 655–675, 10.2307/2297826.

Sanz-Pérez, E. S., C. R. Murdock, S. A. Didas, and C. W. Jones (2016): "Direct Capture of CO_2 from Ambient Air," *Chemical Reviews*, 116, 11840–11876, 10.1021/acs.chemrev.6b00173.

Shayegh, S., V. Bosetti, and M. Tavoni (2021): "Future Prospects of Direct Air Capture Technologies: Insights From an Expert Elicitation Survey," *Frontiers in Climate*, 3, 630893, 10.3389/fclim.2021.630893.

**Online Appendix**