



Working Paper

Technology Neutrality vs. Policy Discrimination: Optimal Policy Design for Competing Green Technologies

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Abstract

The deployment of clean technologies in hard-to-abate sectors is often hindered by high costs and investment risks. Carbon Contracts for Difference (CCfDs) have emerged to mitigate these risks, yet their design raises a central question: should support for competing clean technologies be technology-neutral or technology-specific? We study this question in a setting with two substitutable abatement technologies subject to technology-specific wedges between private and social costs, as well as cost shocks observed by firms but not by the regulator when policy is set. We compare uniform and technology-specific versions of price and quantity instruments. In a quadratic model, technology neutrality distorts the allocation whenever private–social cost wedges differ across technologies, while a neutral quota allows firms to reallocate deployment in response to realized relative costs. A common quota combined with technology-specific subsidies corrects the wedges while preserving this flexibility and therefore outperforms separate technology-specific quotas. The welfare gain from discrimination increases with substitutability between technologies. We micro-found aggregate costs using a distribution of heterogeneous production sites and apply the model to green and blue hydrogen in Europe. In this setting, the value of discrimination depends on the mass of sites near the adoption and technology-choice frontiers. Numerical simulations confirm that targeted support can generate substantial welfare gains. They show that, beyond the quadratic benchmark, the gains from discrimination may differ between price and quantity instruments because prices allow cost shocks to affect total deployment. These results highlight the value of combining technology-neutral competition with targeted corrections of technology-specific market failures.

Keywords: Carbon Contracts for Difference; Technology Neutrality; Investment Risk; Policy Instrument Design; Hydrogen

JEL classification: D82; Q42; Q58

1 Introduction

The energy transition requires the rapid deployment of low-carbon technologies, including many that are still immature, costly, and exposed to considerable uncertainty. This is particularly true in so-called hard-to-abate sectors such as heavy industry and long-distance transport, where several technological solutions are being developed in parallel, often competing to address the same decarbonization challenge. A range of policy instruments has been developed to support the transition, from R&D subsidies to production subsidies, aiming to foster the emergence and competitiveness of green technologies. Among these, Carbon Contracts for Difference (CCfDs) have emerged as a prominent tool in the European Union to bridge the economic gap for these technologies. A key design question arises: Should climate policy be technology-neutral? That is, should governments support all abatement options uniformly, or should they target specific technologies, for instance, those with greater social value or facing higher market barriers?

While the question is general, our motivating example is the current deployment of CCfDs in Europe, particularly in the hydrogen sector. In this context, multiple hydrogen production technologies coexist, such as electrolysis using renewable electricity, fossil-based hydrogen with carbon capture, or pyrolysis, each with different cost structures and levels of technological maturity.

CCfDs have been introduced as a mechanism to reduce carbon-price and revenue risk by guaranteeing a fixed carbon price. By stabilizing expected revenues, they aim to lower the cost of capital and accelerate the deployment of capital-intensive technologies. This rationale is well aligned with a large literature emphasizing the role of financial constraints and uncertainty in the development of clean technologies, particularly for technologies that are still immature and not yet deployed at an industrial scale. However, while CCfDs primarily hedge carbon price risk and can lower financing costs by stabilizing revenues, they do not necessarily correct all technology-specific investment risks or wedges between private and social costs. These frictions may constitute a major barrier to deployment and can vary significantly across technologies. From a policy design perspective, this raises the question of whether a uniform support scheme can deliver an efficient allocation when technologies differ not only in their costs but also in their exposure to financing frictions.

Specific market imperfections, such as technology-specific spillovers or financing constraints, as discussed above, often differ across technologies and may call for differentiated support policies. However, in the face of uncertainty, the risk of backing an ultimately uncompetitive technology strengthens the case for technology neutrality and for leaving allocation choices to the market. To address this trade-off, we develop a partial equilibrium model with two competing abatement technologies. Competition is captured through their degree of substitutability, and the regulator faces asymmetric information regarding their costs. Firms' perceived costs are higher than the technologies' true social costs. Each technology is associated with a specific cost premium, which may reflect financing barriers or positive externalities, and thus justify targeted support. Using this framework, we compare several policy instruments: a single uniform (technology-neutral) price, two technology-specific prices, a technology-neutral quota, and two technology-specific quotas.

Most analytical results are derived within a quadratic version of the model, which allows a systematic comparison of the four policy instruments. In the presence of asymmetric information, the quantities chosen by firms depend on the realization of their private cost shocks, leading to ex post deviations from the regulator's expected allocation. In addition, when cost premiums differ across technologies, technology-neutral instruments induce a systematic distortion in the allocation of abatement efforts, even in expectation. Together, asymmetric information and heterogeneous premiums create a trade-off between ex post flexibility and ex ante targeting.

We show that the welfare gap between a technology-neutral quota and two technology-specific quotas can be decomposed into two effects: (i) the gain from flexibility, as the neutral quota allows the allocation to adjust to realized costs, and (ii) the cost of distortion, since neutrality fails to account for systematic differences in cost premiums. The net welfare difference between the two instruments is equal to the difference between these two effects. Introducing technology-specific subsidies in addition to a common quota eliminates the distortion induced by heterogeneous premiums, while preserving the gains from flexibility. As a result, a uniform quota combined with technology-specific support outperforms a policy based on two separate quotas. Interestingly, the welfare improvement achieved by using technology-specific subsidies in a quantity-based instrument exactly mirrors the improvement from using two differentiated prices instead of a single uniform price.

These results highlight that the two dimensions of policy design, the choice between price and quantity

instruments and the degree of technological discrimination, can be analysed separately under quadratic assumptions. In both cases, the substitutability between technologies plays a key role. In particular, we show that the benefits of discriminating support increase with the degree of substitutability, emphasizing how the intensity of competition between green technologies affects the welfare gains from targeted policies.

We then develop a micro-founded extension of the model, in which polluting sites can be decarbonized using either of two technologies. Each site faces heterogeneous abatement costs for each option, and the joint distribution of these costs determines aggregate supply. At each site, the clean technology with the lowest adjusted cost is adopted if profitable; otherwise, no adoption occurs. We show that the degree of substitutability between technologies is linked to this distribution: when most sites lie “along the diagonal”, that is, when both technologies are close competitors for most sites, substitutability is high, and the cost of choosing the wrong technology becomes more severe. In such cases, discrimination between technologies should be more valuable.

We then calibrate this framework to the hydrogen sector, focusing on the competition between electrolysis (so-called green hydrogen) and CCS-based hydrogen (blue hydrogen). The competition between green and blue hydrogen has been addressed in the energy systems literature, ([Longden et al., 2022](#); [Nagel and Jåstad, 2025](#); [Ueckerdt et al., 2024](#)), highlighting differences in emissions performance, cost structures, and the role of carbon capture efficiency. The model is calibrated using country-level electricity and gas cost variations, together with common non-energy cost components. We abstract from differences in abatement potential and assume that both technologies achieve similar decarbonization levels. Instead of standard blue hydrogen (75% capture), we consider a high-capture variant (95%), more comparable to green hydrogen in emissions performance, but less mature and thus more exposed to investment risk ([Riemer and Duscha, 2022](#)). Consistent with the theoretical predictions, the share of blue hydrogen is significantly higher under targeted policies than under technology-neutral ones under our benchmark calibration.

We also explore how the gains from targeting vary with key parameters. Our numerical results confirm that the benefits of technology-specific support are larger when competition between technologies is more intense, that is, when they are close substitutes across most sites. They also show that the ranking of price and quantity instruments depends on how targeting affects aggregate deployment. Under price instruments, technology-specific support changes the relative attractiveness of the two technologies and therefore reallocates sites toward the targeted technology. But it can also make total adoption more sensitive to technology-specific shocks, especially when many sites are close to the adoption frontier. This additional variation in aggregate quantity reduces the net gain from price discrimination relative to quantity-based targeting.

As a result, the neutral quota complemented with technology-specific subsidies performs best in almost all simulations: it corrects technology-specific wedges while preserving flexibility in the allocation between technologies and keeping aggregate deployment close to the imposed quota. The main exception arises when deviations from the aggregate decarbonization target are relatively inexpensive for the regulator. In that case, the cost of quantity fluctuations is limited and technology-specific prices may outperform quantity-based instruments. Overall, our results highlight the value of combining technology-neutral competition with targeted corrections of technology-specific market failures.

The present work is linked to several strands of the literature: the comparison of policy instruments à la [Weitzman \(1974\)](#); the design of CCfDs and, more generally, firms’ risk aversion; and the financing costs of green technologies.

First, within the vast literature building on the seminal contribution of [Weitzman \(1974\)](#) on comparing price and quantity instruments under asymmetric information, our paper introduces two important extensions. We consider multiple competing green technologies, and we allow for technology-specific externalities, such as financing barriers in our motivating example, that call for differentiated policy interventions. The work of [Fabra and Montero \(2023\)](#) is the most closely related to ours. They also examine the question of technology neutrality under asymmetric information. However, in their framework, discrimination across technologies is justified by the cost of public funds and the welfare gains from third-degree price discrimination. In contrast, in our setting, each technology generates a specific externality (or financing barrier) that distorts private investment incentives. Moreover, we explicitly model competition between green technologies, which is absent from their baseline model.¹ Several other papers within this tradition address related

¹[Fabra and Montero \(2023\)](#) consider an extension with imperfect substitutability, but on the benefit side, their leading motivating example being auctions for solar and wind capacity. In contrast, we model imperfect substitutability on the cost

questions, notably in the context of merging emissions permit markets (Williams III, 2002; Meunier, 2011; Weitzman, 2020). These contributions study the trade-off between the gains from market integration under asymmetric information and countervailing forces that justify market separation. In both Williams III (2002) and Weitzman (2020), this countervailing force stems from imperfect substitutability on the benefit side. In Meunier (2011), it originates from imperfect competition in the product market.

Second, several articles have analysed CCfDs as instruments to reduce the investment risks faced by developers of low-carbon technologies. Richstein and Neuhoﬀ (2022), using corporate finance approaches, analyse how CCfDs help reduce financing costs by securing future revenue streams. They estimate numerically that CCfDs could lower the overall cost of decarbonization by up to 27% in the steel industry. Earlier contributions such as Richstein (2017) and Jeddi et al. (2021) explicitly model risk-averse firms. Richstein (2017) investigates how CCfDs can minimize the cost of subsidies, acting as a costless tool for a risk-neutral regulator to stimulate investment. Jeddi et al. (2021) emphasize how CCfDs can mitigate investor risk while preserving flexibility in the carbon pricing system. Chiappinelli and Neuhoﬀ (2020) considers CCfDs as a way to overcome regulatory time-inconsistency issues. The use of CCfDs for hydrogen is examined by Chaton and Metta-Versmessen (2023), who emphasize that carbon price risk is transmitted to electricity prices, thereby affecting the cost of electrolysis. More broadly, several environmental and energy economics contributions have considered the impact of firm-level risk aversion on investment in clean technologies. Baldursson and Von der Fehr (2004) compares price and quantity regulation in a setting with risk-averse firms, arguing that price-based instruments may outperform quantities by providing more predictable returns. Meunier (2014) examines the role of risk aversion under asymmetric information when choosing a portfolio of technologies, highlighting conditions under which efficient technologies might be excluded from the market due to risk.

To the best of our knowledge, there is no existing analysis on whether CCfDs should be tailored to technology-specific investment risks, an issue that becomes central when technologies diﬀer substantially in their exposure to financial barriers.

Finally, a large body of work has explored the interaction between environmental policy and innovation policy, emphasizing the so-called "double market failure", the coexistence of environmental externalities and knowledge externalities, and the resulting need to complement carbon pricing with R&D or production subsidies (see Ahlvik and van den Bijgaart, 2024, for a recent contribution). To our knowledge, this literature does not explicitly address the question of technology neutrality and targeting. Furthermore, relatively few contributions have focused on financing barriers as a distinct constraint on clean innovation, despite their recognized importance as a major obstacle to innovation (Hall and Lerner, 2010). A few recent papers have nonetheless examined financing issues in more detail in the context of low-carbon technologies, either through theoretical models of endogenous growth (Spiganti et al., 2024) or more micro-level analyses of capital access (e.g., Andersen, 2017; Haas and Kempa, 2023). However, these contributions do not explore whether support should be differentiated across technologies. By contrast, the present work explicitly models technology-specific investment barriers (captured through cost premiums), shows that discrimination can be desirable, and analyses how technological competition shapes the value of targeting.²

In our motivating example, CCfDs address a cost premium that reflects such financing constraints. More generally, however, cost premiums may also stem from other types of externalities. In this paper, we do not model the mechanisms that generate these wedges explicitly. Instead, we treat them as reduced-form representations of a gap between private and social costs, for instance, due to firms' risk aversion. This risk aversion should be understood as a behavioural shortcut: various frictions may underlie it, including imperfect capital markets, limited liability, or informational asymmetries. Ideally, such frictions should be identified and addressed directly through appropriate policy instruments. In their absence, however, investment subsidies may oﬀer a second-best solution to correct distorted incentives and support eﬃcient deployment.

The rest of the article is organized as follows. In Section 2, we present the quadratic model and the instruments to be compared. In Section 3, we proceed with the analytical comparison of instruments. In Section 4, we discuss the application to CCfDs. In Section 5, we develop the micro-founded model, present its calibration, and report the numerical simulations.

side, reflecting competition between technologies to supply abatement, while assuming that emissions reductions are perfect substitutes.

²Financing issues have also been studied from a more applied perspective, particularly in relation to the maturity of clean technologies and their differential access to capital (e.g., Polzin et al., 2021; Ang et al., 2017; Brunnschweiler, 2010).

2 Model

2.1 Set-up

We consider a partial equilibrium model in which two abatement technologies are available indexed by $i \in \{1, 2\}$. The quantity produced with technology $i \in \{1, 2\}$ is q_i , the total quantity is $q = q_1 + q_2$. These quantities should be interpreted as long-term capacities. The total abatement cost, aggregated over price-taking firms, is

$$C(q_1, q_2, \theta_1, \theta_2) = (c_1 + \theta_1)q_1 + (c_2 + \theta_2)q_2 + \frac{\beta_1}{2}q_1^2 + \frac{\beta_2}{2}q_2^2 + \gamma q_1 q_2. \quad (1)$$

where θ_1 and θ_2 are zero-mean cost shocks observed by firms but not by the regulator when the policy instrument is chosen. Because they enter both social and perceived costs, they generate an informational friction but no systematic wedge between private and social costs. We assume that $\mathbb{E}\theta_1 = \mathbb{E}\theta_2 = 0$. Abatement is produced by atomistic price taking firms. The parameter $\gamma \geq 0$ will play a pivotal role in the analysis. It captures imperfect substitutability on the supply side, as the technologies compete for the same polluting sources to be decarbonized or for the same input. A higher γ represents a more intense competition between the two technologies. At the extreme, if $\gamma = \sqrt{\beta_1 \beta_2}$, the two technologies are perfectly substitutable and only one is used. We assume that the cost function is convex, that is, $\gamma < \sqrt{\beta_1 \beta_2}$, and denote by Δ its discriminant:

$$\Delta = \beta_1 \beta_2 - \gamma^2. \quad (2)$$

Abatement generates a public benefit :

$$B(q_1 + q_2) = \left(a - \frac{b}{2}(q_1 + q_2) \right) (q_1 + q_2). \quad (3)$$

The objective of the regulator is to maximize the welfare function :

$$W(q_1, q_2, \theta_1, \theta_2) = B(q_1 + q_2) - C(q_1, q_2, \theta_1, \theta_2). \quad (4)$$

In reality, firms do not internalize all social benefits and costs associated with abatement technologies. Young technologies, in particular, may face financial constraints or generate positive spillovers that are not captured in their private cost functions. To model this divergence, we separately introduce two technology-specific premiums, ρ_1 and ρ_2 , which are known ex ante and enter firms' perceived costs but not social costs. Quantities are chosen as if the cost were

$$\tilde{C}(q_1, q_2, \theta_1, \theta_2) = (c_1 + \rho_1 + \theta_1)q_1 + (c_2 + \rho_2 + \theta_2)q_2 + \frac{\beta_1}{2}q_1^2 + \frac{\beta_2}{2}q_2^2 + \gamma q_1 q_2. \quad (5)$$

Thus, the shocks θ_i determine the value of ex post flexibility, whereas differences in the premiums ρ_i determine the value of technology discrimination.

The gap between social and private costs can stem from various factors, such as knowledge spillovers, unaccounted environmental co-benefits (e.g., improved air quality), or financial frictions that disproportionately affect emerging technologies. The role of these cost differentials, particularly in the context of technology deployment and financing challenges, will be further explored in Section 4 on CCfDs.

We will consider several instruments : a single price, two prices, two quotas or a single quota. For quantity instruments we assume that quotas will be allocated through an auction that clears at the competitive market equilibrium. For a pair of prices p_1 and p_2 , whether directly fixed by the regulator or resulting from an auction, the representative firm maximizes the profit

$$\Pi(p_1, p_2, q_1, q_2, \theta_1, \theta_2) = p_1 q_1 + p_2 q_2 - \tilde{C}(q_1, q_2, \theta_1, \theta_2) \quad (6)$$

The welfare function is concave. However, it is possible that the optimal or market equilibrium consists of only one technology being used. This is the case if the two technologies are different and the substitutability between the two technologies is sufficiently large. We consider that such a case could arise at the local level, but at the sectoral or macro level, the relevant scale of the present model, the two technologies will be used in all cases considered. Section 5 presents a micro-founded version of the model that clarifies this point. In

that model, technologies compete locally to decarbonize polluting sites, which are distributed according to their costs. At the aggregate level, the distribution of sites will determine the substitutability between the two technologies and be linked to γ .

2.2 Instruments and timing

We aim to analyse the pros and cons of technology neutrality. It is worth noting, first, that the optimal allocation could in principle be decentralized through an auction mechanism in which the regulator announces the demand schedule $B'(q_1 + q_2)$ together with subsidies equal to ρ_1 and ρ_2 , thereby correcting for the cost premiums that distort firms' choices. We consider simpler and more realistic instruments. We consider both price- and quantity-based instruments and, for each, compare technology neutrality with technology specificity. Specifically, we examine four instruments: a single uniform price p , two separate prices p_1 and p_2 , a single technology-neutral quota Q , and two technology-specific quotas Q_1 and Q_2 .

The timing is as follows. The regulator knows the distribution of (θ_1, θ_2) and the technology-specific premiums (ρ_1, ρ_2) , but not the realization of the cost shocks when choosing the policy instrument. First, the regulator sets the instrument ex ante. Second, firms observe θ_1 and θ_2 and choose their quantities. Hence, quantities are uncertain from the regulator's ex ante perspective and depend on both the instrument level and the realized cost shocks. The expected values of quantities are denoted with an upper bar, i.e., $\bar{q}_i$.

For each instrument, expected welfare is denoted with a subscript indicating whether it is a price (P) or a quota (Q), and a superscript N for technology neutrality or S for technology specificity. For instance, W_P^N represents the optimal expected welfare under a single price.

With two prices p_1 and p_2 the representative firm maximizes the profit function given by equation (6) and equalizes prices with marginal costs. If both quantities are positive, they solve

$$p_i = \frac{\partial \tilde{C}}{\partial q_i} = c_i + \theta_i + \rho_i + \beta_i q_i + \gamma q_j \text{ for } i, j \in \{1, 2\}, i \neq j \quad (7)$$

The corresponding supply functions are

$$q_i^S(p_1, p_2) = \frac{1}{\Delta} [\beta_j(p_i - c_i - \theta_i - \rho_i) - \gamma(p_j - c_j - \theta_j - \rho_j)] \text{ for } i, j \in \{1, 2\}, i \neq j \quad (8)$$

$$q^S(p_1, p_2) = \frac{1}{\Delta} [(\beta_2 - \gamma)(p_1 - c_1 - \rho_1 - \theta_1) + (\beta_1 - \gamma)(p_2 - c_2 - \rho_2 - \theta_2)] \quad (9)$$

With two quotas there is nothing left to be chosen by firms. With a single neutral quota Q , a market clearing price $\tilde{p}$ ensures that the total supply is equal to the quota: $Q = q_1 + q_2$, with the supply function above with $p_1 = p_2 = \tilde{p}$.

3 Comparison of instruments

We begin by characterizing the optimal allocation and its response to cost shocks, distinguishing between changes in the total abatement level and reallocations across technologies. We then turn to the instruments themselves, quantities and prices, and show how the combination of cost premiums and technological substitutability shapes the benefits of technology-specific support in both cases. The difference between a single quota and two technology-specific quotas illustrates this tension particularly well: it increases with asymmetric information and decreases with the divergence in cost premiums (Proposition 1). Moreover, a single quota combined with differentiated subsidies outperforms a system with two fixed quotas (Proposition 2). Interestingly, the gains from discrimination do not depend on whether price or quantity instruments are used; as a result, the comparison between price and quantity instruments depends solely on the informational structure (Propositions 3 and 4).

We conclude by clarifying the connection with the seminal result of Weitzman (1974), and further analyse the role of technological substitutability in shaping the welfare impacts of policy design.

3.1 Optimal allocation

The optimal allocation q_1^*, q_2^* maximizes welfare, given by eq. (4). If both quantities are positive, the optimal allocation is given, for $i, j \in \{1, 2\}$ with $i \neq j$, by:

$$\begin{aligned} q_i^*(\theta_1, \theta_2) &= \frac{1}{(\beta_1 + b)(\beta_2 + b) - (\gamma + b)^2} [(\beta_j + b)(a - c_i - \theta_i) - (\gamma + b)(a - c_j - \theta_j)] \\ &= \bar{q}_i^* - \frac{(\beta_j + b)\theta_i - (\gamma + b)\theta_j}{(\beta_1 + b)(\beta_2 + b) - (\gamma + b)^2} \end{aligned} \quad (10)$$

Both the total quantity $q^* = q_1^* + q_2^*$ and its allocation vary with the random cost components. The second line isolates the expected optimal quantities from their random components. It is also helpful to think about the choice of quantities in two steps: first, the choice of the total quantity, and second, the choice of its allocation among the two technologies. The allocation step consists of minimizing the total cost for a given total quantity, while the total quantity itself is determined by equating marginal benefit with marginal cost. Following this reasoning, individual quantities could be expressed as functions of the total quantity:

$$q_1^* = \frac{c_2 + \theta_2 - (c_1 + \theta_1)}{\beta_1 + \beta_2 - 2\gamma} + \frac{\beta_2 - \gamma}{\beta_1 + \beta_2 - 2\gamma} q^*. \quad (11)$$

Under uncertainty, both the total optimal quantity and its allocation across technologies vary with the cost shocks. Each of these variations contributes to the welfare gains from improved information. It is worth noting that a change in the total quantity does not translate proportionally into changes in each technology's output. The way this adjustment is distributed depends on the structure of the cost function, in particular the substitutability γ and the comparison between β_1 and β_2 .

In this perspective, distortions arising from cost premiums can affect either the total level of abatement or its allocation across technologies. It is therefore natural to express individual supply curves, given by (8) as functions of the total quantity:

$$q_1^S(p, p) = \frac{c_2 + \theta_2 - (c_1 + \theta_1)}{\beta_1 + \beta_2 - 2\gamma} + \frac{\rho_2 - \rho_1}{\beta_1 + \beta_2 - 2\gamma} + \frac{\beta_2 - \gamma}{\beta_1 + \beta_2 - 2\gamma} q^S. \quad (12)$$

We will consider welfare losses in a number of situations below. There are two properties of our quadratic setting that greatly simplify the comparison of instruments. The first helps isolate the effect of the cost premiums and the distorted choices of quantities. The second helps isolate the effect of asymmetric information. Welfare can be written as the difference between the first best and the distance to the first best quantities:

$$W = W(q_1^*, q_2^*, \theta_1, \theta_2) - \frac{\beta_1 + b}{2} (q_1 - q_1^*)^2 - \frac{\beta_2 + b}{2} (q_2 - q_2^*)^2 - (\gamma + b) (q_1 - q_1^*) (q_2 - q_2^*) \quad (13)$$

And, concerning the random terms, in all cases, each quantity could be written as a sum of its expected value and a random component: $q_i = \bar{q}_i + \epsilon_i$ and expected welfare could then be written as

$$\mathbb{E}W(q_1, q_2, \theta_1, \theta_2) = W(\bar{q}_1, \bar{q}_2, 0, 0) - \mathbb{E} \left[\sum_{i=1,2} \left(\theta_i \epsilon_i + \frac{\beta_i + b}{2} \epsilon_i^2 \right) + (\gamma + b) \epsilon_1 \epsilon_2 \right] \quad (14)$$

Thus, for instance, the expected optimal welfare is

$$\mathbb{E}W(q_1^*, q_2^*, \theta_1, \theta_2) = W(\bar{q}_1^*, \bar{q}_2^*, 0, 0) + \frac{1}{2} \frac{\mathbb{E}[(\beta_2 + b)\theta_1^2 + (\beta_1 + b)\theta_2^2 - 2(\gamma + b)\theta_1\theta_2]}{(\beta_1 + b)(\beta_2 + b) - (\gamma + b)^2} \quad (15)$$

The last term captures the maximum benefit to be obtained from information. This gain can be decomposed into two components related to the variations in the total quantity and in its allocation (cf Appendix A).

3.2 Quotas

As a benchmark, it is useful to consider two quotas. In that case, the quantities are certain and do not depend on cost realizations. The regulator chooses these quotas Q_1 and Q_2 by maximizing expected welfare

$$\max \mathbb{E} [W(Q_1, Q_2, \theta_1, \theta_2)] = W(Q_1, Q_2, 0, 0)$$

The optimal quotas Q_1 and Q_2 , if positive, are equal to the expected optimal quantities $Q_i^* = \bar{q}_i^* = q_i^*(0, 0)$ described in the previous section (cf equation (10)). The two premiums do not influence these quotas.

With all other instruments, the quantities chosen will be random, and the interaction between their random components and the θ_i will determine how well the instrument performs compared to the two quotas, together with the inefficiency introduced by the cost premiums. Remarkably, in our setting, the expected total quantity with each instrument considered will be equal to the expected optimal one, which is the sum of the two optimal quotas.

However, the allocation of this quantity between the two technologies will be distorted by the premiums under technology-neutral instruments.

With a technology-neutral auction, a total abatement quantity Q is fixed and auctioned. The resulting common price $\tilde{p}$ clears the market and satisfies

$$\tilde{p} = \frac{\partial \tilde{C}}{\partial q_1} = \frac{\partial \tilde{C}}{\partial q_2} \quad \text{and} \quad q_1 + q_2 = Q. \quad (16)$$

The price is random and depends on the realization of the cost shocks. Calculations provided in Appendix A.2 show that the optimal quantity is equal to the sum of the two optimal technology-specific quotas: $Q^* = Q_1^* + Q_2^*$.

However, the allocation of this total quantity between the two technologies varies with the random cost components and is distorted by the two premiums.

The quantity produced with technology 1 is such that

$$q_1 = Q_1^* - \frac{\rho_1 - \rho_2}{\beta_1 + \beta_2 - 2\gamma} - \frac{\theta_1 - \theta_2}{\beta_1 + \beta_2 - 2\gamma} \quad (17)$$

Compared to the two-quota system, a single quota allows quantities to adjust more efficiently in response to random cost shocks. However, it introduces an inefficiency due to the presence of cost premiums, which distort the allocation between technologies. These two effects work in opposite directions when comparing the welfare performance of a single quota versus two technology-specific quotas. In the quadratic setting, the structure of the model allows these effects to be disentangled analytically.

Proposition 1 *The welfare difference between an optimal technology-neutral quota and two technology-specific quotas is*

$$W_Q^N - W_Q^S = \frac{1}{2} \frac{\mathbb{E}[(\theta_1 - \theta_2)^2] - (\rho_1 - \rho_2)^2}{\beta_1 + \beta_2 - 2\gamma} \quad (18)$$

While a neutral quota introduces distortion due to uncorrected cost distortion heterogeneity, it allows the allocation between technologies to adjust efficiently in response to shocks. This raises the question of whether it is possible to retain this flexibility without incurring the misallocation costs associated with a uniform instrument. The answer is yes: combining a single technology-neutral auction with technology-specific subsidies (or cost corrections) restores the efficient allocation between technologies while preserving flexibility in the allocation across technologies. The following proposition formalizes this result.

Proposition 2 *Let W_Q^+ denote the maximal expected welfare under a technology-neutral quota complemented with technology-specific subsidies equal to ρ_1 and ρ_2 .*

A technology-neutral quota together with these subsidies outperforms two technology-specific quotas by

$$W_Q^+ - W_Q^S = \frac{1}{2} \frac{\mathbb{E}[(\theta_1 - \theta_2)^2]}{\beta_1 + \beta_2 - 2\gamma}. \quad (19)$$

The welfare gain from adding the technology-specific subsidies to the neutral quota is

$$W_Q^+ - W_Q^N = \frac{1}{2} \frac{(\rho_1 - \rho_2)^2}{\beta_1 + \beta_2 - 2\gamma}, \quad (20)$$

which is increasing in the substitutability parameter γ .

3.3 Prices

We now turn to price-based instruments. In this case, it is always welfare-improving to discriminate and implement technology-specific prices. We begin by quantifying the gain from such discrimination (Lemma 1). The distribution of random cost components does not affect the comparison, since these shocks impact the outcome in the same way under both a single price and two differentiated prices.

Let us first consider two prices. These prices are set ex ante by the regulator, anticipating firms' reaction.

$$0 = \mathbb{E} \left\{ \sum_{j=1,2} \left[B'(q_1 + q_2) - \frac{\partial C}{\partial q_j} \right] \frac{\partial q_j}{\partial p_i} \right\} = \sum_{j=1,2} [B'(\bar{q}_1 + \bar{q}_2) + \rho_j - p_j] \frac{\partial q_j}{\partial p_i} \text{ for } i = 1, 2 \quad (21)$$

The two optimal prices do not depend on random components, and the corresponding expected quantities are equal to the optimal quotas, which were equal to the expected optimal quantities. The optimal prices are simply:

$$p_i^* = B'(\bar{q}^*) + \rho_i \quad (22)$$

Now, with a single price instrument, the regulator needs to account for both distortions and set p^* so that

$$0 = \sum_{i=1,2} \mathbb{E} \left\{ [B'(q_1 + q_2) + \rho_i - p] \frac{\partial q_i}{\partial p} \right\} = \sum_{i=1,2} \left\{ [B'(\bar{q}_1 + \bar{q}_2) + \rho_i - p] \frac{\partial q_i}{\partial p} \right\} \quad (23)$$

Calculations displayed in Appendix A.3 show that the optimal uniform price is a weighted average of the two technology-specific prices:

$$p^* = B'(\bar{q}^*) + \frac{(\beta_2 - \gamma)\rho_1 + (\beta_1 - \gamma)\rho_2}{\beta_1 + \beta_2 - 2\gamma} = \frac{(\beta_2 - \gamma)p_1^* + (\beta_1 - \gamma)p_2^*}{\beta_1 + \beta_2 - 2\gamma}. \quad (24)$$

Lemma 1 *The welfare gain from using two technology-specific prices instead of a single neutral price is*

$$W_P^S - W_P^N = \frac{1}{2} \frac{(\rho_2 - \rho_1)^2}{\beta_1 + \beta_2 - 2\gamma} \quad (25)$$

It is increasing with respect to the substitutability parameter γ .

The gain from discriminating is the same as the gain obtained by introducing two subsidies into a single, technology-neutral auction (cf Proposition 2). The two issues, asymmetric information and distortion, can be considered separately in the quadratic framework. Whether a price or quantity approach should be preferred therefore depends on informational considerations.

3.4 Price versus quantity

The comparison between price and quantity instruments in our setting is driven solely by asymmetric information; the distortion introduced by risk premiums plays no role here. The welfare difference depends on three key factors: the variability of cost shocks, the slope of the marginal benefit function (which governs the cost of aggregate abatement errors), and the structure of the cost function, in particular the parameter γ , which captures the degree of substitutability between technologies. The parameter γ affects the comparison in two distinct ways: it influences both the variation in total abatement and the efficiency of allocation across

technologies. Under price instruments, whether uniform or differentiated, both effects are present. With two quotas, both sources of flexibility are shut down; with a single quota, the aggregate adjustment is muted, but reallocation across technologies remains possible.

The following two propositions provide formal comparisons between price and quantity instruments. We then revisit the decomposition to interpret the role of γ in shaping these results.

Proposition 3 *The difference in expected welfare between two prices and two quotas is:*

$$W_P^S - W_Q^S = \frac{1}{2\Delta} \mathbb{E} [\beta_2 \theta_1^2 + \beta_1 \theta_2^2 - 2\gamma \theta_1 \theta_2] - \frac{b}{2\Delta^2} \mathbb{E} [((\beta_2 - \gamma)\theta_1 + (\beta_1 - \gamma)\theta_2)^2] \quad (26)$$

Finally, the difference between a uniform price and a uniform quota is the same as the difference between two prices and a uniform quota combined with subsidies. This comparison can be framed as a [Weitzman \(1974\)](#) comparison.

Proposition 4 *The difference in expected welfare between a single price and a single quantity is:*

$$W_P^N - W_Q^N = \frac{1}{2\Delta^2} \left[\frac{\Delta}{\beta_1 + \beta_2 - 2\gamma} - b \right] \mathbb{E} \left[\left((\beta_2 - \gamma)\theta_1 + (\beta_1 - \gamma)\theta_2 \right)^2 \right] \quad (27)$$

$$= \frac{1}{2\Gamma^2} [\Gamma - b] \mathbb{E} \left[\left(\frac{(\beta_2 - \gamma)\theta_1 + (\beta_1 - \gamma)\theta_2}{\beta_1 + \beta_2 - 2\gamma} \right)^2 \right] \quad (28)$$

in which

$$\Gamma = \frac{\beta_1 \beta_2 - \gamma^2}{\beta_1 + \beta_2 - 2\gamma}$$

This last expression emphasizes the connection to the seminal comparison established by [Weitzman \(1974\)](#): The sign of the welfare difference depends on the relative slope of marginal cost and marginal benefit, while the magnitude of the difference is proportional to the variance of the uncertainty term. The parameter Γ is the slope of the aggregate marginal cost curve, and the term inside the expectation corresponds to the effective shock to aggregate marginal cost, a weighted sum of the random cost components affecting the two technologies.

Finally, the comparison between the two-price and two-quota schemes in Proposition 3 can be decomposed into two components: (i) the classic price–quantity trade-off à la Weitzman, as captured in Proposition 4, and (ii) a gain from trade due to reallocation between technologies. The first term of the comparison (26) can be explicitly written as the sum of these two components:

$$\begin{aligned} \frac{1}{2\Delta} \mathbb{E} [\beta_2 \theta_1^2 + \beta_1 \theta_2^2 - 2\gamma \theta_1 \theta_2] &= \underbrace{\frac{1}{2\Gamma} \mathbb{E} \left[\left(\frac{(\beta_2 - \gamma)\theta_1 + (\beta_1 - \gamma)\theta_2}{\beta_1 + \beta_2 - 2\gamma} \right)^2 \right]}_{\text{Aggregate shock effect}} \\ &\quad + \underbrace{\frac{1}{2} \frac{\mathbb{E}[(\theta_1 - \theta_2)^2]}{\beta_1 + \beta_2 - 2\gamma}}_{\text{Reallocation effect}}. \end{aligned} \quad (29)$$

And the comparison between specific instruments can then be written as:

$$W_P^S - W_Q^S = W_P^N - W_Q^N + \frac{1}{2} \frac{\mathbb{E}[(\theta_1 - \theta_2)^2]}{\beta_1 + \beta_2 - 2\gamma}. \quad (30)$$

The first term captures the effect of the aggregate shock on the total quantity, while the second term reflects the gain from reallocation between technologies, and depends on the dispersion of the individual shocks. The second term increases with γ , as greater substitutability between technologies enhances the benefit of reallocating abatement effort in response to heterogeneous cost realizations. The effect of γ on the first term is more nuanced: with identical and independently distributed uncertainties, the variance of the aggregate shock increases with γ as the weights placed on individual shocks become more unequal. However,

this effect is partially mitigated by the increase in the aggregate cost slope Γ , which dampens the system's sensitivity to shocks.

In the symmetric case, with $\beta_1 = \beta_2 = \beta$, the comparison (28) greatly simplifies to

$$W_P^N - W_Q^N = \frac{1}{2(\beta + \gamma)^2} \left[\frac{\beta + \gamma}{2} - b \right] \mathbb{E}[(\theta_1 + \theta_2)^2]$$

Although the relationship is hump-shaped rather than monotonic in γ , the expression shows that stronger technological interactions expand the range over which price regulation dominates. We therefore expect the relative merit of prices to rise with the intensity of competition between the two technologies.

4 Carbon contracts for difference

A key motivation for CCfDs is to reduce the investment risk faced by developers of green infrastructure. As highlighted by [Richstein and Neuhoﬀ \(2022\)](#), CCfDs can lower the cost of capital for clean technologies by shifting risk from private investors to the regulator. While the design of CCfDs raises multiple policy challenges, this paper focuses on one central issue: technology neutrality in the presence of heterogeneous risk profiles. In particular, we consider the case where competing green technologies face different risk premiums due to differences in cost volatility and exposure to carbon price uncertainty.

We assume that the regulator is risk-neutral, while firms together with their financial backers act *as if* they were risk-averse. In this setting, the risk-adjusted cost of each technology includes a premium that depends on the perceived variance of returns. The relevant risks include both the volatility of the CO₂ price and the uncertainty about technology-specific costs. Importantly, the risks underlying the premiums ρ_i are distinct from the cost shocks θ_i introduced earlier. The shocks θ_i are cost realizations observed by firms before they make their production and technology choices, but not by the regulator when the policy instrument is set. By contrast, the uncertainties underlying ρ_i remain unresolved when investment decisions are made and affect firms' certainty-equivalent costs. We do not model these primitive risks explicitly; instead, we represent their effect through reduced-form technology-specific premiums.

Let σ^2 denote the variance of the CO₂ price, and σ_1^2 and σ_2^2 the variances associated with the cost risks of technologies 1 and 2, respectively. We assume that firms apply mean–variance preferences, with a coefficient λ capturing their degree of risk aversion. As a result, the cost premium associated with technology $i = 1, 2$ is given by:³

$$\rho_i = \lambda(\sigma^2 + \sigma_i^2). \quad (31)$$

In the absence of public intervention, a representative firm maximizes

$$\Pi(q_1, q_2) = \bar{p}_{CO_2}(q_1 + q_2) - \lambda(\sigma^2 + \sigma_1^2)q_1 - \lambda(\sigma^2 + \sigma_2^2)q_2 - C(q_1, q_2).$$

A CCfD sets a guaranteed forward CO₂ price and compensates firms for deviations from that price. This policy eliminates CO₂ price risk (at no fiscal cost in expectation), reducing each premium to $\lambda\sigma_i^2$. In other words, CCfDs do not eliminate all risk, but they remove the common risk component linked to carbon price volatility.

Under a technology-neutral CCfD, a single guaranteed carbon price p is offered to all firms. Under a technology-specific CCfD, each technology receives its own guaranteed price p_i , and firms maximize profits as described in equation (6), with $\rho_i = \lambda\sigma_i^2$.

In principle, it is optimal to set differentiated CCfD prices that are tailored to the technology-specific cost premiums. These prices would fully correct for both the CO₂ price risk and the cost risk. Even if a uniform CCfD price is used, the underlying cost risks should still be incorporated into the price formula. This leads to the expression in equation (24), where the optimal price reflects a weighted average of risk-adjusted costs.

By contrast, a naive or “myopic” CCfD that ignores cost risks would simply set a price $\hat{p} = B'(q_1 + q_2)$, equal to the expected CO₂ price, rather than the price p^* defined in equation (24). It would therefore induce

³This can be derived from a mean–variance utility function. For each unit to be decarbonized, a risk-averse firm compares the certainty equivalent profits from each option. With technology 1, the firm compares $\mathbb{E}[p - c_1 - \gamma q_2] - \lambda(\sigma^2 + \sigma_1^2)$ to the analogous expression for technology 2.

an inefficiently low level of investment. An analytical expression for the gain from moving from such a myopic CCfD to an optimized one is derived in Appendix B.

$$W_P^N - \hat{W} = \frac{\lambda^2}{2(\Gamma + b)} \left[\frac{(\beta_1 - \gamma)\sigma_2^2 + (\beta_2 - \gamma)\sigma_1^2}{\beta_1 + \beta_2 - 2\gamma} \right]^2.$$

This expression illustrates how the interaction between technology-specific cost risks and technological competition (captured by γ) amplifies the welfare loss from using a naive CCfD. While an optimal uniform CCfD cannot fully correct for asymmetries between technologies, it still internalizes the cost risks and efficiently weights them, thereby substantially improving welfare.

To sum up, we view CCfDs as forward carbon price contracts that can serve multiple purposes:

- (i) correcting for a too-low expected EU ETS price to ensure alignment with decarbonization goals;
- (ii) reducing financing costs by derisking revenue streams exposed to carbon price volatility;
- (iii) supporting investment in immature technologies whose risk profile translates into high capital costs.

The first objective would be moot in a perfectly aligned policy environment where EU ETS expectations were consistent with climate targets. The second has been the most prominent justification in both policy and academic discussions. The third, however, is less often acknowledged despite being central to the economics of innovation under uncertainty, and justifies further raising the CCfD price. The formula above captures the welfare gains from explicitly accounting for these financing-related risks, and shows how an optimal CCfD would set a higher support level than a myopic version targeting only carbon price volatility.

Crucially, the case for technology-specific CCfDs stems from a fourth observation: financing conditions vary systematically across technologies, reflecting differences in maturity and investor familiarity. This reinforces the idea that technology neutrality may be suboptimal in the presence of heterogeneous investment risks.

Finally, regarding the choice of instruments, it is important to recognize that CCfDs, while framed as price guarantees, operate within a policy framework that is fundamentally quantity-driven. This hybrid nature has implications for the neutrality debate and for the design of optimal support schemes under uncertainty.

While CCfDs are often discussed in the literature as price-based instruments, offering a guaranteed carbon price to investors, their implementation in practice follows a quantity-driven logic. In the EU, for instance, sectoral decarbonization objectives are defined in quantity terms from the outset, such as the 55% reduction target for industrial emissions by 2030, and CCfDs are used as a tool to achieve these goals. Auctions are organized to allocate contracts across technologies and firms, effectively determining the volume of supported abatement and introducing a competitive selection process. From this perspective, CCfDs combine elements of price support (via the strike price) with quantity-based allocation, further complicating the notion of neutrality in instrument design.

5 Numerical illustration

In this section, we develop a micro-founded version of the model based on heterogeneous abatement costs across polluting sites. Our objective is to assess numerically the welfare effects of different policy instruments in a more realistic setting. We consider the case of competing hydrogen production technologies, in particular, green hydrogen (via electrolysis) and blue hydrogen (from natural gas with carbon capture), as a representative example of early-stage clean technology competition.

We proceed in three steps. First, we explore the model analytically, without asymmetric information, focusing on the case of price instruments (neutral and specific) and establishing connections with the quadratic formulation. Second, we calibrate the model for the case of competition among hydrogen production technologies. Third, we conduct numerical simulations and sensitivity analyses to examine how the welfare gains from price discrimination vary with key parameters, in particular, the intensity of technological competition.

5.1 Framework

We consider a stylized setting in which a continuum of polluting sites (one site being normalized to 1 tCO₂) must adopt one of two clean technologies, or remain inactive. These sites are heterogeneous in their abatement costs, characterized by a joint distribution $f(c_1, c_2)$, where c_1 and c_2 denote the costs of adopting

technologies 1 and 2, respectively. In the hydrogen application, c_1 and c_2 combine investment and operating costs, whose heterogeneity across sites primarily reflects differences in local input prices. The analytical discussion below initially abstracts from asymmetric information by setting $\theta_1 = \theta_2 = 0$. In the numerical simulations, θ_i is introduced as a technology-wide additive cost shock common to all sites using technology i , whose realization varies across Monte Carlo draws. By contrast, ρ_i is fixed across sites and draws and shifts firms' perceived adoption costs systematically.

If we denote by $\mathcal{D}_1$ and $\mathcal{D}_2$ the sets of sites using technology 1 and 2 respectively, the quantities produced are

$$q_i = \int_{\mathcal{D}_i} f(c_1, c_2) dc_1 dc_2 \text{ for } i = 1, 2 \quad (32)$$

and welfare can be written as:

$$W = B(q_1 + q_2) - \int_{\mathcal{D}_1} c_1 f(c_1, c_2) dc_1 dc_2 - \int_{\mathcal{D}_2} c_2 f(c_1, c_2) dc_1 dc_2. \quad (33)$$

Given prices p_1 and p_2 , each site chooses technology 1, technology 2, or no adoption so as to maximize its perceived net benefit, accounting for the site-invariant premiums ρ_1 and ρ_2 :

- Technology 1 is chosen if $p_1 - (c_1 + \rho_1)$ is positive and greater than $p_2 - (c_2 + \rho_2)$
- Technology 2 is chosen if $p_2 - (c_2 + \rho_2)$ is positive and greater than $p_1 - (c_1 + \rho_1)$
- No adoption occurs if both net profits are negative.

At the market equilibrium, the two domains are

$$\mathcal{D}_1(p_1, p_2) = \{c_1 \leq p_1 - \rho_1 \text{ and } c_2 \geq c_1 + (p_2 - p_1) - (\rho_2 - \rho_1)\}, \quad (34)$$

$$\mathcal{D}_2(p_1, p_2) = \{c_2 \leq p_2 - \rho_2 \text{ and } c_1 \geq c_2 - (p_2 - p_1) + (\rho_2 - \rho_1)\} \quad (35)$$

The optimal allocation consists of a total quantity of abatement q^* efficiently allocated among sites with domains corresponding to the equilibrium ones with prices $p_i = B'(q^*) + \rho_i$ for $i = 1, 2$. Indeed, without asymmetric information such a pricing system would decentralize the optimum.

The situation is depicted in Figure 1: the left panel shows the optimal allocation and the right panel displays the market equilibrium, without correction for the premiums. Two types of misallocation can arise: first, failing to decarbonize a site that should be (grey area); second, using the wrong technology (hatched area). The second kind of mistake relates to the intensity of competition between technologies which was represented by γ in the quadratic framework and is here linked to the distribution of sites. The connection between the two models could be made more explicit by looking at derivatives of quantities with respect to prices.

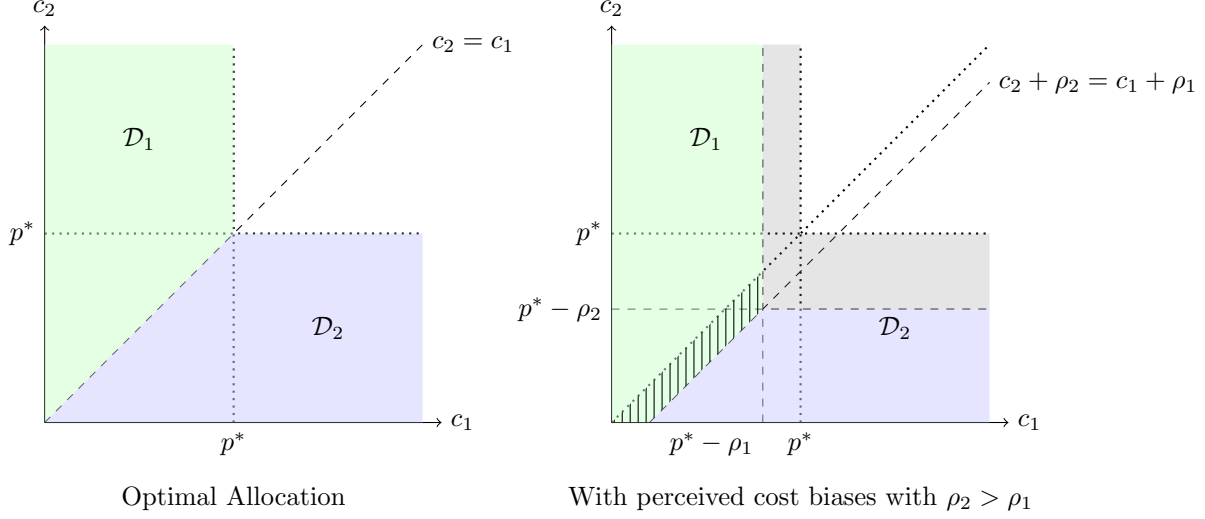


Figure 1: Distribution of abatement across sites at the optimum and biased equilibrium

For two prices p_1 and p_2 , the quantity abated with technology 1 is

$$q_1(p_1, p_2) = \int_{c_1=0}^{p_1-\rho_1} \int_{c_2=c_1+\rho_1-p_1+p_2-\rho_2}^{+\infty} f(c_1, c_2) dc_2 dc_1.$$

To understand the intensity of competition between the two technologies, we examine how the adoption of one technology responds to the price of the other. In particular, we focus on the derivative

$$\frac{\partial q_1}{\partial p_2} = - \int_0^{p_1-\rho_1} f(c_1, c_1 + \rho_1 - p_1 + p_2 - \rho_2) dc_1 \quad (36)$$

This derivative captures the density of agents located at the indifference frontier between the two technologies, i.e., those for whom small changes in the price differential can tip the choice. It serves as a natural micro-founded counterpart to the interaction term γ in the quadratic cost formulation. With the quadratic specification, the sensitivity of technology 1 adoption to the price of technology 2 is:

$$\frac{\partial q_1}{\partial p_2} = - \frac{\gamma}{\beta_1 \beta_2 - \gamma^2}$$

The absolute value of this expression increases with γ , reflecting stronger substitutability between technologies. This parallels the behaviour of the cross-derivative in the distributed-cost model, which becomes large when the cost distribution is concentrated near the indifference frontier $c_1 \simeq c_2$. This correspondence suggests that the benefit of price discrimination increases with the intensity of competition, whether captured analytically through γ or geometrically through the density of f around the frontier of indifference. A complementary parallel between the coefficients β_i , own-price supply responses, and the density of sites along the adoption frontiers is developed in Appendix C.

To conclude the analytical exploration of the micro-founded setting, we provide the counterpart to equation (24), which characterizes the optimal uniform price in the quadratic model. When a single price is applied to both technologies, it must strike a balance between the two sources of distortion. The optimal price is therefore implicitly defined by the following equation:

$$p = B'(q) + \frac{\rho_1 \int_{c_2=p-\rho_2}^{+\infty} f(p-\rho_1, c_2) dc_2 + \rho_2 \int_{c_1=p-\rho_1}^{+\infty} f(c_1, p-\rho_2) dc_1}{\int_{c_2=p-\rho_2}^{+\infty} f(p-\rho_1, c_2) dc_2 + \int_{c_1=p-\rho_1}^{+\infty} f(c_1, p-\rho_2) dc_1}$$

Comparing this expression to equation (24) in the quadratic case further clarifies the connection between the two models. In both settings, the optimal uniform neutral price corresponds to a weighted average of the marginal benefit and the cost distortions induced by applying a single instrument across heterogeneous technologies.

5.2 Calibration

Today, most hydrogen is produced via Steam Methane Reforming (SMR) from natural gas without CO₂ capture, resulting in “grey” hydrogen, which serves as our carbon-based reference. We calibrate our model to the competition between two low-carbon alternatives: the first is green hydrogen (technology 1), produced through the electrolysis of water using low-carbon electricity; the second is blue hydrogen (technology 2), produced from SMR combined with carbon capture and storage (CCS).

The calibration is conducted in the context of hydrogen production in Europe, using a dataset describing existing hydrogen production costs and capacities by country (Clean Hydrogen Observatory, 2024). The model is calibrated to capture the key dimensions of competition between low-carbon technologies. Its primary goal is to compare public policy instruments under cost heterogeneity. It is not intended to provide a granular or comprehensive view of the hydrogen technology mix in 2030.

5.2.1 Low-carbon hydrogen technology costs by 2030

To calibrate the costs used in our model, we rely on data from Clean Hydrogen Observatory (2025), available for 26 European countries for the year 2024. For green hydrogen, we consider the costs of grid electrolysis, which allows for a higher load factor of the electrolyser but may imply access to more expensive low-carbon electricity. In this database, CAPEX and additional OPEX are common across all countries, while wholesale electricity costs, grid fees, and taxes differ across countries. For blue hydrogen, we consider the costs of hydrogen reforming with carbon capture from the same database. CAPEX, CO₂ capture costs, and additional OPEX are common across all countries, while natural gas costs are country-specific. Overall, energy inputs represent a major share of the costs of low-carbon hydrogen technologies, vary notably across regions, and constitute our main source of cost heterogeneity.

The reported costs correspond to 2024 values, not to 2030 values, and our source does not provide projections. We therefore use European cost-reduction assumptions from the Hydrogen Tracker Tool of International Energy Agency (2025). Between 2024 and 2030, the cost of blue hydrogen from natural gas decreases by 13% on average. The cost of renewable hydrogen produced through electrolysis decreases, on average across the different production sources, by approximately 40%. We therefore apply these reductions uniformly to all blue and green hydrogen technology costs in order to obtain country-level cost projections for 2030.

On average across countries, the resulting costs are 4.3 €/kgH₂ for green hydrogen and 3.5 €/kgH₂ for blue hydrogen. This corresponds to a rather optimistic assumption for green hydrogen compared with other estimates. Overall, the expected cost of green hydrogen in 2030 lies between 1.77 and 6 €/kg, while the expected cost of blue hydrogen lies between 2.4 and 4.3 €/kg. The dominant technology is therefore expected to vary across sites depending on their location within Europe, according to whether local conditions favour cheaper renewable electricity or cheaper natural gas.

We distinguish these production-cost figures from incremental abatement costs. Let L_i denote the de-risked production cost of technology i . We assume a common and constant avoided cost of grey hydrogen, $g = 1.50$ €/kgH₂, excluding carbon costs, so that the incremental cost entering the adoption and welfare equations is $c_i = L_i - g$. This illustrative benchmark is informed by the European Commission’s 2020 estimate for fossil-based hydrogen production in the EU (European Commission, 2020); it is not intended as a forecast of European production costs in 2030. The same value of g applies across sites, technologies, sensitivity scenarios, and shock realizations. The production-cost statistics reported above remain in gross terms.

5.2.2 Uncertainty parameters

Uncertainty due to information asymmetry θ The technologies considered in our application are still at an early stage of deployment, so their future production costs remain highly uncertain. We therefore interpret θ_i broadly as a technology-specific deviation in expected production costs about which project developers have better information than the regulator when the policy instrument is set. This informational advantage may concern expected long-run energy prices, capital costs, construction and operating performance, electrolyser efficiency, or the costs and availability of CO₂ capture, transport, and storage. Firms

do not necessarily know future costs perfectly, but they possess project- and technology-specific information that is not fully available to the regulator.

These shocks are distinct from the risks underlying the premiums ρ_i . The realization of θ_i represents information incorporated into firms' technology and production choices, whereas ρ_i captures the cost of uncertainty that remains unresolved when investment decisions are made.

Direct empirical estimates of this informational advantage are not available. We therefore use the historical variability of technology-specific energy input prices as an observable benchmark for the scale of the shocks. This proxy captures only one component of the underlying cost uncertainty and should not be interpreted as a complete structural calibration of θ_i . We consequently complement the benchmark with sensitivity analyses that vary the magnitude and composition of the shocks.

To construct this proxy, we rely on historical semi-annual industrial price data from Eurostat for the European Union (Eurostat, 2026b,a). Based on these observations, the electricity price exhibits a volatility, defined as the standard deviation relative to the mean price, of approximately 28%, while the natural gas price exhibits a volatility of approximately 37%.

In our calibration framework, the baseline average cost components for energy inputs are retrieved directly from our database. The mean electricity cost for green hydrogen in 2030 is estimated at 1.83 €/kgH₂, and the baseline natural gas cost for blue hydrogen is estimated at 2.33 €/kgH₂. The standard deviations of the cost uncertainty terms are derived by applying the respective historical volatilities directly to these baseline costs:

$$\begin{aligned}\sigma_{\theta_1} &= 0.28 \times 1.83 \approx 0.51 \text{ €/kgH}_2, \\ \text{and } \sigma_{\theta_2} &= 0.37 \times 2.33 \approx 0.86 \text{ €/kgH}_2.\end{aligned}$$

We summarize the resulting uncertainty distributions as:

$$\begin{aligned}\theta_1 &\sim \mathcal{N}(0, 0.51^2) \quad \text{for green hydrogen,} \\ \text{and } \theta_2 &\sim \mathcal{N}(0, 0.86^2) \quad \text{for blue hydrogen.}\end{aligned}$$

Uncertainty related to risk aversion ρ_i In addition to energy uncertainty, we consider a premium associated with firms' risk aversion. This term affects individual firms, which are assumed to be risk-averse, but not the social planner. For each technology i , the premium is calibrated as:

$$\rho_i = \lambda (\kappa_{\text{CO}_2} + \kappa_{K,i}),$$

where λ denotes a normalized risk-aversion coefficient, while κ_{CO_2} and $\kappa_{K,i}$ are the common and technology-specific monetary risk components, respectively.

We adopt a unitary risk-aversion coefficient, $\lambda = 1$, so that ρ_i is the sum of these components, both expressed in €/kgH₂. These components are calibrated directly in monetary units rather than estimated from the primitive variances introduced in Section 4.

We use historical EU ETS price volatility as an order-of-magnitude benchmark for the common monetary component, not as a structural estimate of a financing premium. Based on annual average prices over the 2021–2026 period, we estimate the volatility of the carbon price at 20% for our calibration.

Assuming an expected EU ETS price of 150 €/tCO₂ in 2030, the corresponding standard deviation is:

$$\sigma_{\text{pCO}_2}^{2030} = 0.20 \times 150 = 30 \text{ €/tCO}_2.$$

Given a carbon intensity of 0.01 tCO₂/kgH₂ for grey hydrogen (IEA, 2024), this term captures uncertainty in the expected carbon benefits from using low-carbon hydrogen technologies instead of grey hydrogen. The corresponding uncertainty expressed per unit of low-carbon hydrogen is:

$$\sigma_{\text{pCO}_2}^{\text{H}_2} = 30 \text{ €/tCO}_2 \times 0.01 \text{ tCO}_2/\text{kgH}_2 = 0.30 \text{ €/kgH}_2.$$

For the numerical illustration and calibration, we set $\kappa_{\text{CO}_2} = \sigma_{\text{pCO}_2}^{\text{H}_2} = 0.30 \text{ €/kgH}_2$.

The technology-specific financing premium, $\kappa_{K,i}$, is calibrated from the financing component embedded in the capital costs of green and blue hydrogen. The reported capital-cost components in [Clean Hydrogen](#)

Observatory (2024) are assumed to be annualized over a 20-year project lifetime using a baseline WACC of 5%.

For green hydrogen, the capital-cost component in 2030 is 2.0 €/kgH₂. Removing the financing component associated with the 5% WACC yields a derisked capital cost of approximately 1.30 €/kgH₂. The difference between the initial and derisked costs is interpreted as the financing risk premium:

$$\kappa_{K,1} = 2.0 - 1.30 \simeq 0.7 \text{ €/kgH}_2.$$

For blue hydrogen, the initial capital-cost component is 1.23 €/kgH₂ in 2030, also calculated using a 5% WACC over 20 years. Removing this initial financing component gives a derisked capital cost of approximately 0.77 €/kgH₂. The financing component initially embedded in the data is therefore:

$$1.23 - 0.77 = 0.46 \text{ €/kgH}_2.$$

This amount is removed when constructing the derisked cost used by the social planner. However, private investment in blue hydrogen is assumed to face substantially higher financing risk. Conventional carbon capture systems generally achieve capture rates of around 75%, whereas advanced systems may reach approximately 95% (Riemer and Duscha, 2022). To compare blue and green hydrogen while abstracting from residual emissions, we assume that blue hydrogen relies on these advanced high-capture-rate technologies. Their higher costs and greater technological and operational uncertainty justify the use of a higher WACC.

We therefore replace the 5% WACC initially embedded in the blue hydrogen cost with a 15% WACC, while retaining the same 20-year project lifetime and the same underlying derisked investment cost. This increases the annualized capital-cost component from approximately 0.77 to 2.46 €/kgH₂. The financing risk premium faced by private blue hydrogen producers is consequently:

$$\kappa_{K,2} = 2.5 - 0.8 = 1.7 \text{ €/kgH}_2$$

The benchmark premiums are therefore

$$\rho_1 = 0.30 + 0.70 = 1.00 \text{ €/kgH}_2, \quad \rho_2 = 0.30 + 1.70 = 2.00 \text{ €/kgH}_2.$$

The derisked capital costs retained as inputs for the social planner are:

$$K_1 = 1.28 \text{ €/kgH}_2, \quad K_2 = 0.77 \text{ €/kgH}_2.$$

These are capital-cost components of gross production costs, not the complete incremental costs c_i . The avoided grey-hydrogen cost is subtracted once from the complete derisked production cost L_i .

5.2.3 Decarbonization parameters

Total hydrogen production in Europe and geographical distribution We base our country-level calibration of hydrogen demand on the TYNDP 2024 report (European Network of Transmission System Operators for Gas, 2024), which provides projected annual hydrogen demand by country in 2030 for the hydrogen infrastructure level. For the 26 countries retained in our model, aggregate hydrogen demand amounts to approximately 18.6 MtH₂/year. These country-specific values are used to calibrate the geographical distribution of hydrogen demand in the model.

Based on these country-level cost inputs, we construct a discretized 50 × 50 grid with green-hydrogen costs on one axis and blue-hydrogen costs on the other. Each country's projected hydrogen demand is initially assigned to the cell corresponding to its combination of green and blue hydrogen costs. Each cell is then interpreted as a production unit characterized by a specific pair of technology costs and an associated hydrogen quantity.

Since the original country-level data generate a limited number of discrete cost combinations, we apply a Gaussian filter with a standard deviation of 10 cells. This procedure distributes hydrogen demand across neighbouring cost combinations, thereby generating the continuous heterogeneity of production units considered in the model, while preserving aggregate hydrogen demand. The resulting distribution is represented in Figure 2.

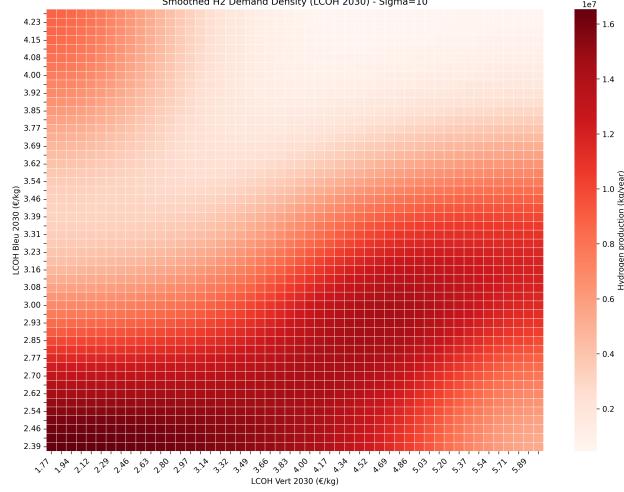


Figure 2: Smoothed distribution of hydrogen demand according to projected derisked production costs in 2030. The x-axis represents the derisked LCOH of green hydrogen, while the y-axis represents the derisked LCOH of blue hydrogen. The intensity of each cell indicates the annual hydrogen demand associated with the corresponding combination of production costs, expressed in kgH₂/year. The initial country-level distribution is smoothed using a Gaussian filter with a standard deviation of 10 cells. The axes display gross derisked production costs L_i ; incremental abatement costs used in the model are $c_i = L_i - g$.

We assume that replacing grey hydrogen with green or blue hydrogen does not induce a geographical reallocation of production. This reflects the high transportation costs of hydrogen and the tendency to locate production close to consumption centres (FCHJU, 2021). Each production unit can therefore either continue producing grey hydrogen or fully decarbonize its associated hydrogen demand using a single low-carbon technology, either green or blue hydrogen.

Decarbonization target The European Union has set a 55% emission reduction target for 2030 through the “Fit for 55” legislative package, aiming for climate neutrality by 2050 (European Commission, 2021). Accordingly, we define a decarbonization target Q^* equal to 55% of the projected European annual hydrogen demand, i.e 10.2 Mt of hydrogen per year.

Decarbonization benefit The decarbonization benefit function $B(q)$ is defined relative to a social planner’s target. The planner aims to achieve a decarbonisation quantity of Q^* , corresponding to 55% of total grey hydrogen production. The function is calibrated so that Q^* corresponds to the expected first-best quantity in the absence of uncertainty. Deviations from this target are valued according to the slope of the benefit function. We assume a quadratic specification of the form $B(q) = (a - bq/2)q$, where q denotes the quantity of decarbonized hydrogen, and a and b are parameters to be calibrated.

In our main scenario, we first compute the carbon price P^* required to achieve the 55% decarbonization target under perfect information (i.e., $\rho_i = \theta_i = 0$). Using incremental costs net of the common grey-hydrogen cost, this yields a carbon price of 140 €/tCO₂. Given that replacing grey hydrogen avoids approximately 0.01 tCO₂/kgH₂, the carbon price corresponds to a marginal decarbonization value of:

$$P^* = 140 \text{ €/tCO}_2 \times 0.01 \text{ tCO}_2/\text{kgH}_2 = 1.4 \text{ €/kgH}_2.$$

From this, we derive the parameters a and b by solving the following system:

$$P^* = a - bQ^*, \quad \text{and} \quad bQ^* = \frac{P^*}{e}, \quad \text{which implies} \quad a = P^* \left(1 + \frac{1}{e}\right).$$

Assuming an illustrative elasticity of $e \simeq 0.5$, we obtain:

$$b = \frac{P^*}{eQ^*} \simeq 2.6 \times 10^{-10} \text{ €/kgH}_2^2,$$

$$a = P^* \left(1 + \frac{1}{e}\right) = 4.3 \text{ €/kgH}_2.$$

The choice of e , and hence of the parameter b , is admittedly delicate. It aims to represent, in a stylized manner, the social cost of missing a decarbonization target, which in reality results from a complex political and societal process. The value used here is illustrative. The values of P^* , Q^* , a , and b reported above correspond to the main scenario and are recalibrated in the sensitivity analyses when the underlying assumptions are modified.

All reported carbon prices are net of avoided grey-hydrogen production costs.

Finally, Table 1 summarizes all calibrated parameters used in the model.

Parameter	Meaning	Calibrated value	Source
K_1	Derisked common capital-cost component of green hydrogen	1.28 €/kgH ₂	Clean Hydrogen Observatory (2024) and 2030 projections
K_2	Derisked common capital-cost component of blue hydrogen	0.77 €/kgH ₂	Clean Hydrogen Observatory (2024) and 2030 projections
v_1	Variable energy-cost component of green hydrogen LCOH	[0.69, 4.98] €/kgH ₂	Clean Hydrogen Observatory (2024) and 2030 projection
v_2	Variable energy-cost component of blue hydrogen LCOH	[1.59, 3.51] €/kgH ₂	Clean Hydrogen Observatory (2024) and 2030 projection
g	Avoided grey-hydrogen production cost, excluding carbon costs	1.50 €/kgH ₂	Illustrative benchmark, European Commission (2020)
θ_1	Technology-specific cost shock for green hydrogen	$\mathcal{N}(0, 0.51^2)$ €/kgH ₂	Electricity-price volatility (Eurostat, 2026a)
θ_2	Technology-specific cost shock for blue hydrogen	$\mathcal{N}(0, 0.86^2)$ €/kgH ₂	Natural-gas-price volatility (Eurostat, 2026b)
λ	Risk-aversion coefficient	1	Unitary baseline assumption
$\kappa_{K,1}$	Risk premium for green hydrogen	0.70 €/kgH ₂	Internal calculation based on a 5% WACC
$\kappa_{K,2}$	Risk premium for blue hydrogen (high-capture variant)	1.70 €/kgH ₂	Internal calculation based on a 15% WACC
κ_{CO_2}	Risk premium associated to the carbon price	0.30 €/kgH ₂	EU ETS price volatility (ICAP, 2026)
Q^*	Decarbonization target	10.2 MtH ₂ /year	European Network of Transmission System Operators for Gas (2024)
(a, b)	Net benefit-function parameters	(4.30, 2.6×10^{-10})	Internal calibration

Table 1: Summary of the key parameters used in the model calibration.

5.3 Simulation methodology

We develop a Python-based algorithm to simulate, for different policy scenarios, the total level of hydrogen decarbonization, the breakdown between blue and green hydrogen on the grid, the level of the public policy instrument depending on its nature, and the expected welfare from the regulator’s perspective.

We examine four different types of instruments: price-based versus quantity-based, and technology-neutral versus technology-specific. We also consider a suboptimal “naive” CCfD, and a technology-neutral quota with targeted subsidies. For neutral and technology-specific price instruments, the regulator maximizes mean welfare. Quantity instruments implement the effective calibration quota Q^* ; technology-specific quantities use the deterministic first-best allocation.⁴ Six scenarios are considered:

- (0) The reference scenario corresponds to a naive instrument, similar to the one presented in the section on CCfDs. The proposed price equals the original deterministic calibration price, selected to meet the nominal 55% target, plus the common carbon-price risk component. This price does not internalize the risk associated with the fixed costs of low-carbon technologies.
- (1) The first scenario corresponds to a price-based, technology-neutral instrument. The regulator sets a uniform carbon price, identical for both low-carbon technologies.
- (2) In the second scenario, the regulator is allowed to set two distinct carbon prices, one for each technology, thus implementing a technology-specific price instrument.
- (3) The technology-neutral quota fixes total deployment at the decarbonization target Q^* and allows the technology mix to respond to realized costs.
- (4) The technology-specific quantity benchmark fixes the site-level technology allocation obtained in the deterministic calibration.
- (5) The fifth scenario builds upon the third by maintaining a quantity-based, technology-neutral framework but complementing it with targeted subsidies equal to each technology’s estimated risk premium.

AI assistance. Codex (OpenAI) assisted with checking, adapting and rerunning copies of the simulation code, and with plotting the site distributions from the calibration inputs.

5.4 Results

5.4.1 Benchmark without asymmetric information

We start with the no-asymmetric-information case as a benchmark. This exercise isolates the pure effect of correcting technology-specific wedges and verifies that, in the absence of informational frictions, price and quantity implementations are equivalent. It also provides a useful way to visualize where technology-specific support operates in the spatial distribution of sites. In this benchmark, firms and the regulator share the same information: $\theta_1 = \theta_2 = 0$.⁵

⁴For a given price p or quota Q , the asymmetric-information simulations use 300 Monte Carlo draws of (θ_1, θ_2) , centred at zero and shared across instruments. For each draw, we compute the market equilibrium, including the equilibrium price under quantity instruments, and identify which technology is used in each cell. Ex post welfare is then calculated for each draw, and expected welfare is obtained by averaging across the 300 draws.

⁵Because the shocks enter costs linearly and have zero mean, this benchmark yields the same expected allocation and welfare as a setting in which the shocks exist but are unobserved when decisions are made, so that neither firms nor the regulator can condition their choices on the realizations. The two settings nevertheless differ ex post, since realized welfare remains stochastic in the latter case.

Scenario	Welfare (bn €)	Price (€/tCO ₂)	Green Share	Blue Share
0. CCfD naive	7.10	170.0	10.6%	0.0%
1. Price Neutral	19.44	324.0	43.3%	17.3%
2. Price Specific	21.16	(242.0, 342.0)	24.4%	36.4%
3. Quantity Neutral	19.44	324.4	43.3%	17.3%
4. Quantity Specific	21.16	—	24.4%	36.4%
5. Quantity N. + Sub.	21.16	(239.4, 339.4)	24.4%	36.4%

Table 2: Comparison of scenarios without asymmetric information ($\theta_1 = \theta_2 = 0$).

Table 2 reports the welfare levels obtained under the different instruments. Moving from the naive CCfD to an optimized neutral instrument generates a large welfare gain, showing that even a technology-neutral policy must account for the risk-adjusted cost of low-carbon technologies. The equivalence between price and quantity implementations is also verified: technology-neutral prices and quotas yield the same allocation and welfare, while technology-specific prices, technology-specific quotas, and a neutral quota combined with technology-specific subsidies all implement the same allocation. The remaining welfare difference therefore measures the pure gain from discrimination, i.e. from correcting the heterogeneous wedges across technologies. The benefit from discrimination without asymmetric information is equal to:

$$W_Q^S - W_Q^N = W_P^S - W_P^N \simeq 1.72 \text{ bn } \text{€}.$$

Figure 3 illustrates the corresponding allocation of sites. Technology-neutral support leads to a relatively low adoption of blue hydrogen. Technology-specific support shifts a substantial mass of sites toward blue hydrogen, either from green hydrogen along the technology-choice frontier, or from the polluting technology along the blue-hydrogen adoption frontier. This spatial reallocation helps interpret the welfare gain from discrimination: it is large when many sites are located near the frontier between the two clean technologies or near the blue-hydrogen adoption frontier, so that correcting the wedge changes the technology choice for a significant share of sites.

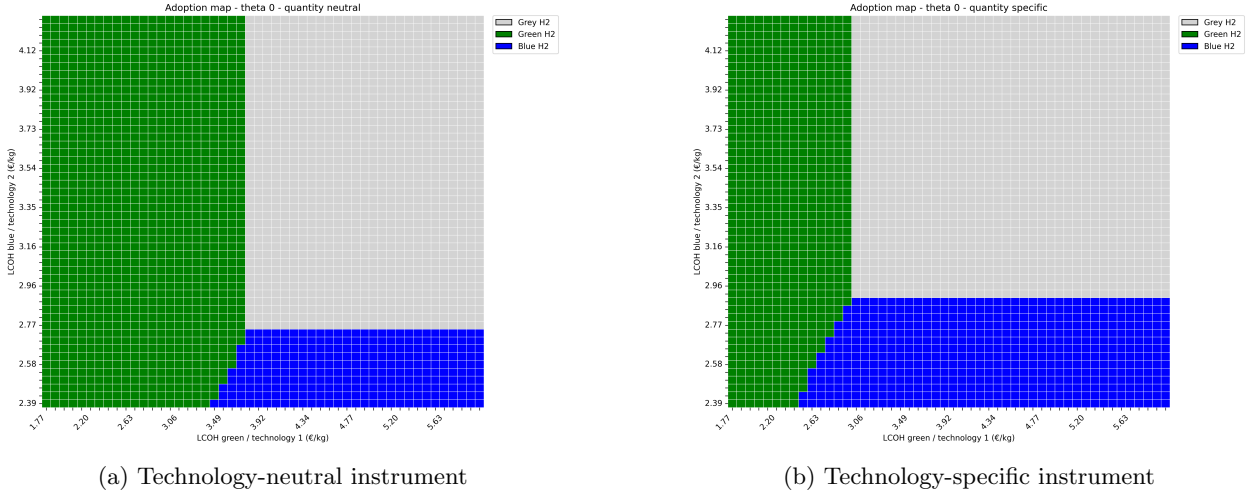


Figure 3: Allocation of technologies across sites in the absence of asymmetric information.

5.4.2 Asymmetric information and the ranking of instruments

We now introduce asymmetric information. The equivalence between price and quantity implementations no longer holds, because price instruments let total deployment vary with cost shocks, while quantity instruments keep aggregate deployment close to the imposed quota in the discretized numerical implementation.

Scenario	Welfare (bn)
0. CCfD naive	9.47
1. Price Neutral	21.19
2. Price Specific	21.79
3. Quantity Neutral	21.25
4. Quantity Specific	21.16
5. Quantity N + sub	22.84

Table 3: Comparisons of Scenarios in the benchmark calibration

Table 3 summarizes the results. The neutral quota combined with technology-specific subsidies, W_Q^+ , delivers the highest expected welfare. It combines the two desirable features that are separated in the other instruments: it corrects the heterogeneous technology wedges, as technology-specific prices do, while maintaining direct control over aggregate deployment, as quantity instruments do.

The comparison between the neutral quota and technology-specific quotas can be read through the decomposition in Proposition 1:

$$W_Q^N - W_Q^S = (W_Q^+ - W_Q^S) - (W_Q^+ - W_Q^N) \simeq 1.69 - 1.59 = 0.10 \text{ bn } \text{€}.$$

The first term captures the value of allowing the allocation between technologies to respond to cost realizations, corresponding to eq. (19) in the quadratic setting. The second captures the cost of leaving technology-specific wedges uncorrected, corresponding to eq. (20). Their near cancellation explains why the neutral and technology-specific quotas deliver similar expected welfare in the benchmark.

Comparing these results with the no-asymmetric-information benchmark also helps interpret the informational component of each instrument. For technology-specific quotas, expected welfare is essentially unchanged. This is expected: the shocks are common to all sites within a technology, so they do not change the cost-minimizing allocation of fixed technology-specific quantities; with mean-zero shocks, their expected effect cancels out. For neutral quotas, by contrast, asymmetric information has positive value in the benchmark because the market-clearing auction reallocates the fixed aggregate quantity between green and blue hydrogen according to realized relative costs.

The interpretation is less direct for price instruments. Prices also allow firms to react to realized costs, but they do so by changing both the technology mix and total deployment. The former margin is valuable, while the latter may be costly when aggregate deployment deviates from the decarbonization target.

5.4.3 Discrimination gains under price and quantity instruments

The benchmark simulation also reveals a difference with the quadratic model. In the quadratic setting, the gain from discrimination is independent of the choice between price and quantity instruments: $W_P^S - W_P^N = W_Q^+ - W_Q^N$ (cf Proposition 2 and Lemma 1). In the micro-founded calibration, this equality no longer holds. The gain from discrimination is larger under the quantity-based instrument: in the benchmark, $W_Q^+ - W_Q^N$ is approximately 1.59 bn €, whereas $W_P^S - W_P^N$ is approximately 0.61 bn €.

The reason is that price discrimination affects not only the allocation between technologies, but also the variability of total deployment. Specific prices correct the wedge in favour of blue hydrogen, but they also make adoption more sensitive to shocks affecting this technology. This additional variability reduces the net welfare gain from price discrimination.

Additional simulations in which only one source of asymmetric information is activated confirm this interpretation (Table D.3 in the Appendix). The gap between price and quantity discrimination is mostly driven by shocks to blue hydrogen, while shutting down blue-hydrogen uncertainty largely restores the similarity between the two discrimination gains.

This result is consistent with the allocation maps (Figures 2 and 3). A substantial mass of sites lies close to the blue-hydrogen adoption frontier. Hence shocks to blue hydrogen costs can move many sites in or out of decarbonized production under price instruments, increasing the variability of total deployment. A neutral quota with targeted subsidies avoids this cost: it corrects the technology-specific wedge while keeping aggregate deployment fixed (Appendix C provides a formal discussion and relates this mechanism to the quadratic setting and the results of Propositions 3 and 4).

5.4.4 Sensitivity analysis

We organize the sensitivity analysis around the mechanisms identified above. We first vary the size of the wedges through the risk-aversion parameter. We then modify the spatial distribution of sites, which governs the intensity of competition between technologies. Finally, we vary the decarbonization target and the curvature of the benefit function, which affect the set of marginal sites and the cost of aggregate quantity fluctuations.

Table 4 reports, for each sensitivity exercise, the welfare gain from discrimination under price instruments and under the neutral quota with targeted subsidies. Across the main sensitivity specifications, mean discrimination gains remain positive for both price and quantity instruments, although the price gains are small in the low-risk-aversion, low-elasticity and low-target cases. The gain is generally larger for the neutral quota with targeted subsidies than for technology-specific prices, confirming the benchmark mechanism: targeted subsidies correct the technology-specific wedge without increasing the variability of aggregate deployment. The only case in which technology-specific prices become the best-performing instrument is the high-elasticity specification. In that case, the gain from discrimination under quantities remains slightly larger, but the cost of aggregate quantity fluctuations is sufficiently low for prices to dominate in levels.

Scenario	$W_P^S - W_P^N$	$W_Q^+ - W_Q^N$	$Q \text{ gain} - P \text{ gain}$	Best instrument
Benchmark	0.61	1.59	0.98	W_Q^+
Risk aversion $\lambda = 0.5$	0.02	0.41	0.39	W_Q^+
Risk aversion $\lambda = 1.5$	1.72	3.23	1.51	W_Q^+
Edge-concentrated density	0.31	1.35	1.05	W_Q^+
Diagonal-concentrated density	0.68	1.67	0.99	W_Q^+
Decarbonization target 40%	0.03	1.16	1.12	W_Q^+
Decarbonization target 70%	1.10	1.78	0.68	W_Q^+
Net elasticity 0.16	0.02	1.59	1.57	W_Q^+
Net elasticity 1.5	1.14	1.59	0.44	W_P^S

Table 4: Welfare gains from technology discrimination under alternative calibrations. Values are in billion euros.

First, increasing risk aversion strengthens the case for technology-specific support. A higher λ magnifies the wedges between private and social costs, especially for blue hydrogen, and therefore increases the welfare cost of technology-neutral policies. This sensitivity mainly affects the value of discrimination, while the informational component remains largely unchanged because the distribution of cost shocks is held fixed. The discrimination gain remains larger under the neutral quota with targeted subsidies than under technology-specific prices, and this gap increases with risk aversion.

Second, we run two additional simulations in which the distribution of sites is modified, either by concentrating sites along the diagonal or by moving them toward the edges of the cost space. The results confirm the role of local competition between technologies. When more sites are located near the relevant adoption and technology-choice frontiers, small changes in relative support induce larger reallocations across technologies. The gain from discrimination therefore rises with the intensity of competition between green and blue hydrogen. The spatial sensitivity also confirms that the ranking of price and quantity instruments depends on whether these reallocations mainly affect the technology mix or aggregate deployment.

Third, we vary the decarbonization target. Increasing the target expands the set of sites that must be decarbonized and therefore changes the relevant margins of adoption. The gains from discrimination increase with the target: as the low-carbon market becomes larger, correcting technology-specific wedges affects a larger mass of sites. At the same time, technology-specific prices perform increasingly well relative to the neutral quota with targeted subsidies. This reflects the calibration of the benefit function: for a given elasticity, a higher target implies a flatter marginal benefit schedule, i.e. a lower value of b . Deviations in total deployment are therefore less costly, which makes price instruments more attractive. This last mechanism is

isolated more directly in the next sensitivity exercise, where we vary the curvature of the benefit function.

Finally, we vary the curvature of the benefit function while holding the calibration point fixed. The low- and high-elasticity cases imply net elasticities of approximately 0.16 and 1.45, respectively, compared with approximately 0.48 in the benchmark. Since $bQ^* = P^*/e$, a higher net elasticity corresponds to a smaller absolute slope b and makes aggregate quantity deviations less costly around the calibration point. Price instruments therefore become more attractive. In the high-elasticity case, technology-specific prices are the best-performing instrument, confirming that their weaker performance in the benchmark is driven by the welfare cost of aggregate quantity fluctuations.

6 Conclusion

This paper studies the design of support instruments for the deployment of competing abatement technologies under uncertainty. We focus on a trade-off at the core of technology-neutral policy design. Leaving firms free to choose between technologies preserves flexibility when they observe technology-specific cost shocks that the regulator does not observe. However, if private incentives differ from social costs in a technology-specific way, uniform support distorts the technology mix. The quadratic model makes this trade-off transparent. In the case of quantity instruments, a technology-neutral quota preserves ex post flexibility, while technology-specific quotas correct wedges but fix the allocation across technologies. A neutral quota complemented with technology-specific subsidies combines both advantages: it corrects heterogeneous premiums while keeping the allocation flexible. Under price instruments, differentiated prices correct the same wedges, and the value of discrimination increases with the substitutability between technologies.

The quadratic benchmark also clarifies the comparison between prices and quantities. In that setting, the choice between price and quantity instruments can be separated from the degree of technological discrimination. The micro-founded simulations show that this separability need not hold more generally. When support is price-based, targeting changes not only the relative attractiveness of green and blue hydrogen but also the sensitivity of aggregate deployment to technology-specific shocks. In the benchmark calibration, technology-specific prices move sites toward blue hydrogen and increase the variability of total deployment. This additional aggregate variability reduces the net gain from price discrimination. As a result, the neutral quota complemented with technology-specific subsidies is the best-performing instrument in almost all simulations. The main exception arises when deviations from the aggregate decarbonization target are relatively inexpensive for the regulator; in that case, technology-specific prices can outperform quantity-based instruments.

Applied to CCfDs, the analysis suggests that a uniform carbon-price guarantee may be insufficient when competing clean technologies differ in maturity, risk exposure, or financing barriers. CCfDs can stabilize revenues and reduce common carbon-price risk, but technology-specific cost premiums may remain. The relevant design issue is therefore not simply whether to choose winners, but how to combine competition across technologies with corrections for identified market failures. In our framework, this points toward instruments that preserve a common competitive allocation mechanism while allowing differentiated support when technology-specific wedges are well documented.

Several simplifying assumptions define the scope of the analysis. First, we assume that the regulator can observe or estimate the technology-specific premiums. In practice, these wedges are uncertain and difficult to quantify ex ante, which complicates the design of targeted support. Future work could endogenize the regulator’s information through monitoring, data acquisition, or learning about technology-specific risks. Second, we assume that green and blue hydrogen are fully substitutable in terms of emissions reductions. The numerical exercise therefore focuses on a high-capture variant of blue hydrogen, comparable to green hydrogen in abatement performance. It should not be read as a case for blue hydrogen in general, nor as a prediction of the blue-green hydrogen mix by 2030. Standard blue hydrogen, methane leakage, imperfect capture performance, and technological lock-in could substantially alter the policy ranking. Incorporating uncertainty over the effective decarbonization rate is therefore an important direction for future research.

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CRedit authorship contribution statement

Albin Kasser: Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing.

Guy Meunier: Methodology, Formal analysis, Writing – original draft, Writing – review & editing.

Declaration of competing interests

The authors declare no known competing interests.

Data and code availability

The data and simulation code supporting the results of this study are available for peer review through [Mendeley Data](#).

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

ChatGPT (OpenAI) was used to assist with manuscript writing and simulation coding. The authors reviewed and edited all AI-assisted material and take full responsibility for the manuscript.

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A Quadratic specification

A.1 Preliminaries

Here, we drop the random components and provide the expression of welfare, optimal quantities, and prices for $\theta_1 = \theta_2 = 0$. To analyse the cost induced by the two premiums it is helpful to introduce the total cost function

$$\mathcal{C}(Q) = \min C(q_1, q_2) \text{ s.t. } q_1 + q_2 = Q$$

Assuming that both quantities are positive, these quantities solve

$$c_1 + \beta_1 q_1 + \gamma q_2 = c_2 + \beta_2 q_2 + \gamma q_1$$

Replacing q_2 with $Q - q_1$ gives the optimal allocation $\phi_1(Q)$:

$$\phi_1(Q) = \frac{\beta_2 - \gamma}{\beta_1 + \beta_2 - 2\gamma}Q - \frac{c_1 - c_2}{\beta_1 + \beta_2 - 2\gamma} \quad (\text{A.1})$$

$$\phi_2(Q) = \frac{\beta_1 - \gamma}{\beta_1 + \beta_2 - 2\gamma}Q + \frac{c_1 - c_2}{\beta_1 + \beta_2 - 2\gamma} \quad (\text{A.2})$$

indeed $\phi_2(Q) = Q - \phi_1(Q)$.

Then, the total cost could be written as a quadratic function of the total quantity Q :

$$\mathcal{C}(Q) = \mathcal{C}_0 + \mathcal{C}_1 \cdot Q + \frac{\Gamma}{2}Q^2. \quad (\text{A.3})$$

The coefficients are obtained as follows: $\mathcal{C}_0$ by plugging $\phi_1(0)$ and $\phi_2(0)$. The first- and second-order coefficient can be obtained by straightforward calculations, or by looking at the derivative of the total cost, which is equal to the partial derivatives: $\mathcal{C}'(Q) = c_1 + \beta_1\phi_1 + \gamma\phi_2$. It gives

$$\mathcal{C}_0 = -\frac{(c_1 - c_2)^2}{2(\beta_1 + \beta_2 - 2\gamma)}; \mathcal{C}_1 = \frac{(\beta_2 - \gamma)c_1 + (\beta_1 - \gamma)c_2}{\beta_1 + \beta_2 - 2\gamma}; \Gamma = \frac{\beta_1\beta_2 - \gamma^2}{\beta_1 + \beta_2 - 2\gamma} \quad (\text{A.4})$$

Indeed, for small Q the non-negativity constraints would be binding and the above expressions would not hold. This is why $\mathcal{C}_0 < 0$ while $\mathcal{C}(0)$ is zero.

We will make use of these coefficients when considering aggregate quantities and the corresponding price. It considerably eases the calculations and the exposition. It can be used to decompose welfare by isolating the misallocation of the total quantity:

$$\begin{aligned} W(q_1, q_2) &= B(q_1 + q_2) - \mathcal{C}(q_1 + q_2) - \frac{\beta_1}{2}(q_1 - \phi_1)^2 - \frac{\beta_2}{2}(q_2 - \phi_2)^2 - \gamma(q_1 - \phi_1)(q_2 - \phi_2) \\ &= B(q_1 + q_2) - \mathcal{C}(q_1 + q_2) - \frac{\beta_1 + \beta_2 - 2\gamma}{2}(q_1 - \phi_1(q_1 + q_2))^2 \end{aligned} \quad (\text{A.5})$$

Then, the optimal quantities obtained in the main text (10) can also be obtained as $q_i^* = \phi_i(Q^*)$ in which Q^* solves $B'(Q) = \mathcal{C}'(Q)$ and is thus equal to $(a - \mathcal{C}_1)/(\Gamma + b)$.

A.2 Technology-neutral auction

Proof of Proposition 1

We first provide the expressions of the quantities with a single quota, then show that the optimal quota is equal to the sum of the two optimal specific quotas, and, finally, derive the comparison (18).

With a single quantity Q , the price $\tilde{p}$ clears the market and solves:

$$Q = \frac{1}{\Delta} [(\beta_1 + \beta_2 - 2\gamma)\tilde{p} - (\beta_2 - \gamma)(c_1 + \rho_1 + \theta_1) - (\beta_1 - \gamma)(c_2 + \rho_2 + \theta_2)]$$

so

$$\tilde{p} = \frac{\Delta}{\beta_1 + \beta_2 - 2\gamma}Q + \frac{\beta_2 - \gamma}{\beta_1 + \beta_2 - 2\gamma}(c_1 + \rho_1 + \theta_1) + \frac{\beta_1 - \gamma}{\beta_1 + \beta_2 - 2\gamma}(c_2 + \rho_2 + \theta_2)$$

and substituting the expression of $\tilde{p}$ into

$$q_1 = \frac{1}{\Delta} [(\beta_2 - \gamma)\tilde{p} - \beta_2(c_1 + \rho_1 + \theta_1) + \gamma(c_2 + \rho_2 + \theta_2)]$$

gives

$$\begin{aligned} q_1 &= \bar{q}_1 - \frac{1}{\Delta} \left[\beta_2\theta_1 - \gamma\theta_2 - (\beta_2 - \gamma) \left(\frac{\beta_2 - \gamma}{\beta_1 + \beta_2 - 2\gamma}\theta_1 + \frac{\beta_1 - \gamma}{\beta_1 + \beta_2 - 2\gamma}\theta_2 \right) \right] \\ &= \bar{q}_1 - \frac{1}{\Delta} \left[\theta_1 \frac{\beta_2(\beta_1 + \beta_2 - 2\gamma) - (\beta_2 - \gamma)^2}{\beta_1 + \beta_2 - 2\gamma} - \theta_2 \frac{\gamma(\beta_1 + \beta_2 - 2\gamma) + (\beta_2 - \gamma)(\beta_1 - \gamma)}{\beta_1 + \beta_2 - 2\gamma} \right] \\ &= \bar{q}_1 - \frac{\theta_1 - \theta_2}{\beta_1 + \beta_2 - 2\gamma} \end{aligned}$$

and by symmetry $q_2 = \bar{q}_2 + (\theta_1 - \theta_2)/(\beta_1 + \beta_2 - 2\gamma)$

Remark: these expressions could be obtained more directly from market equilibrium equations together with $q_1 + q_2 = Q$.

Expected welfare is then

$$\begin{aligned} \mathbb{E}W &= W(\bar{q}_1, \bar{q}_2, 0, 0) + \mathbb{E} \left[\theta_1 \frac{\theta_1 - \theta_2}{\beta_1 + \beta_2 - 2\gamma} + \theta_2 \frac{\theta_2 - \theta_1}{\beta_1 + \beta_2 - 2\gamma} \right] \\ &\quad - \mathbb{E} \left[\frac{\beta_1 + b}{2} \left(\frac{\theta_1 - \theta_2}{\beta_1 + \beta_2 - 2\gamma} \right)^2 + \frac{\beta_2 + b}{2} \left(\frac{\theta_2 - \theta_1}{\beta_1 + \beta_2 - 2\gamma} \right)^2 + (\gamma + b) \frac{\theta_1 - \theta_2}{\beta_1 + \beta_2 - 2\gamma} \frac{\theta_2 - \theta_1}{\beta_1 + \beta_2 - 2\gamma} \right] \\ &= W(\bar{q}_1, \bar{q}_2, 0, 0) + \frac{1}{2} \frac{\mathbb{E}[(\theta_1 - \theta_2)^2]}{\beta_1 + \beta_2 - 2\gamma} \end{aligned} \quad (\text{A.6})$$

Choice of the optimal quota: The choice of the optimal quota Q maximizes expected welfare. Random components and their welfare effects can be isolated, so we drop the notation of random components since they do not intervene in the choice of Q . The optimal quota maximizes $W(\bar{q}_1(Q), \bar{q}_2(Q), 0, 0)$ in which

$$\bar{q}_1 = \frac{\beta_2 - \gamma}{\beta_1 + \beta_2 - 2\gamma} Q - \frac{c_1 - c_2}{\beta_1 + \beta_2 - 2\gamma} - \frac{\rho_1 - \rho_2}{\beta_1 + \beta_2 - 2\gamma} = \phi_1(Q) - \frac{\rho_1 - \rho_2}{\beta_1 + \beta_2 - 2\gamma} \quad (\text{A.7})$$

$$\bar{q}_2 = \frac{\beta_1 - \gamma}{\beta_1 + \beta_2 - 2\gamma} Q + \frac{c_1 - c_2}{\beta_1 + \beta_2 - 2\gamma} + \frac{\rho_1 - \rho_2}{\beta_1 + \beta_2 - 2\gamma} = \phi_2(Q) + \frac{\rho_1 - \rho_2}{\beta_1 + \beta_2 - 2\gamma} \quad (\text{A.8})$$

The first two terms correspond to the optimal allocation of the quota, and the last one is the distortion induced by the cost premiums. From the expression of welfare (A.5) obtained in the preliminaries:

$$W(\bar{q}_1(Q), \bar{q}_2(Q)) = W(\phi_1(Q), \phi_2(Q)) - \frac{1}{2} \frac{(\rho_1 - \rho_2)^2}{\beta_1 + \beta_2 - 2\gamma}. \quad (\text{A.9})$$

The optimal quota then corresponds to the one that maximizes welfare without distortion and thus coincides with the sum of the two optimal quotas, which is also the expected optimal quantity.

$$Q^* = \frac{a - \mathcal{C}_1}{\Gamma + b} = \frac{(\beta_2 - \gamma)(a - c_1) + (\beta_1 - \gamma)(a - c_2)}{(\beta_1 + b)(\beta_2 + b) - (\gamma + b)^2}$$

The comparison (18) is obtained by using equation (A.6) and (A.9).

A.3 Prices

Proof of Lemma 1

We proceed as follows. We first derive optimal welfare under two prices and show that the prices are such that expected quantities equal the optimal quotas. We then consider a single price and show that it yields the same expected total quantity as the two-price instrument. Finally, we derive the welfare comparison between one and two prices and obtain the expression for the optimal uniform price.

With two prices p_1 and p_2 , from equation (8):

$$q_1 = \bar{q}_1(p_1, p_2) - \frac{\beta_2 \theta_1 - \gamma \theta_2}{\Delta} \quad \text{and} \quad q_2 = \bar{q}_2 - \frac{\beta_1 \theta_2 - \gamma \theta_1}{\Delta}$$

Expected welfare is then, using equation (14):

$$\begin{aligned} \mathbb{E}W &= W(\bar{q}_1, \bar{q}_2, 0, 0) + \mathbb{E} \left[\theta_1 \frac{\beta_2 \theta_1 - \gamma \theta_2}{\Delta} + \theta_2 \frac{\beta_1 \theta_2 - \gamma \theta_1}{\Delta} \right] \\ &\quad - \mathbb{E} \left[\frac{\beta_1 + b}{2\Delta^2} (\beta_2 \theta_1 - \gamma \theta_2)^2 + \frac{\beta_2 + b}{2\Delta^2} (\beta_1 \theta_2 - \gamma \theta_1)^2 + \frac{\gamma + b}{\Delta^2} (\beta_2 \theta_1 - \gamma \theta_2)(\beta_1 \theta_2 - \gamma \theta_1) \right] \\ &= W(\bar{q}_1, \bar{q}_2, 0, 0) + \frac{1}{2\Delta} \mathbb{E} [\beta_2 \theta_1^2 + \beta_1 \theta_2^2 - 2\gamma \theta_1 \theta_2] - \frac{b}{2\Delta^2} \mathbb{E} [((\beta_2 - \gamma)\theta_1 + (\beta_1 - \gamma)\theta_2)^2] \end{aligned} \quad (\text{A.10})$$

The two prices are chosen to maximize the first term $W(\bar{q}_1(p_1, p_2), \bar{q}_2(p_1, p_2), 0, 0)$, and thus will be such that $\bar{q}_i(p_1, p_2) = Q_i^*$.

Let us now find the expressions of the two prices. They will be set so that

$$B'(\bar{q}_1 + \bar{q}_2) = p_i - \rho_i = \frac{\partial C}{\partial q_i}$$

With the quadratic setting, they are equal to

$$p_i = p + \rho_i = B'(\bar{Q}^*) + \rho_i = \frac{\Gamma a + b\mathcal{C}_1}{\Gamma + b} + \rho_i = \frac{\Delta a + b[(\beta_2 - \gamma)c_1 + (\beta_1 - \gamma)c_2]}{(\beta_1 + b)(\beta_2 + b) - (\gamma + b)^2} + \rho_i$$

With a single price, the two quantities are as above with $p_1 = p_2$, and the effect of random components on total welfare is the same as above. The optimal price is chosen to maximize $W(\bar{q}_1(p, p), \bar{q}_2(p, p), 0, 0)$. And making use of the expression of welfare (A.5) again:

$$W(\bar{q}_1(p, p), \bar{q}_2(p, p)) = B(\bar{q}_1 + \bar{q}_2) - \mathcal{C}(\bar{q}_1 + \bar{q}_2) - \frac{\beta_1 + \beta_2 - 2\gamma}{2}(\bar{q}_1 - \phi_1(\bar{q}_1 + \bar{q}_2))^2$$

The last term is the cost due to the cost premiums. It could be obtained from first-order conditions:

$$c_1 + \rho_1 + \beta_1 q_1 + \gamma q_2 = c_2 + \rho_2 + \beta_2 q_2 + \gamma q_1$$

replacing $q_2 = q - q_1$ gives $q_1 = \phi_1(q) - (\rho_1 - \rho_2)/(\beta_1 + \beta_2 - 2\gamma)$ as with the technology-neutral quota (A.7), substituting this in the above expression of welfare gives the comparison (25) in Lemma 1.

Expression of the neutral price

The price is then chosen to maximize $B(q) - \mathcal{C}(q)$ and is such that the expected total quantity is equal to the expected optimal quantity, and is equal to the expected total quantity obtained with two technology-specific prices.

The expression for the price is obtained from the first-order condition

$$B'(\bar{q}_1 + \bar{q}_2) \cdot \left(\frac{d\bar{q}_1}{dp} + \frac{d\bar{q}_2}{dp} \right) = \frac{\partial C}{\partial q_1} \frac{d\bar{q}_1}{dp} + \frac{\partial C}{\partial q_2} \frac{d\bar{q}_2}{dp} = (p - \rho_1) \frac{d\bar{q}_1}{dp} + (p - \rho_2) \frac{d\bar{q}_2}{dp}.$$

Therefore,

$$p = B'(\bar{Q}^*) + \frac{\rho_1 \frac{d\bar{q}_1}{dp} + \rho_2 \frac{d\bar{q}_2}{dp}}{\frac{d\bar{q}_1}{dp} + \frac{d\bar{q}_2}{dp}} = B'(\bar{Q}^*) + \frac{(\beta_2 - \gamma)\rho_1 + (\beta_1 - \gamma)\rho_2}{\beta_1 + \beta_2 - 2\gamma}$$

A.4 Prices vs quantities

Proof of Proposition 3

The difference in expected welfare between two prices and two quotas is the sum of the last two terms in (A.10).

Proof of Proposition 4

The comparison between a single price and a single quantity could be obtained from the two previous formulas and cast as a Weitzman comparison with the corresponding aggregated uncertainty and marginal cost slope.

B CCfDs

We sketch the environment in which the CCfD is designed and how it is implicitly embedded into the benefit function. The EU-ETS could be represented by a sector supplying abatement x at a random cost $C_{ETS}(x)$. The additional abatement x is done after investment q_1 and q_2 . The randomness of C_{ETS} translates into a random benefit from investment q_1 and q_2 . The benefit function $B(q_1 + q_2)$ is then the expectation of a random function with the coefficient a being the expected value of a random benefit $\tilde{a}$.

It is optimal to wait until the true abatement cost is known before setting the CO₂ price. $p_{CO_2} = \tilde{a} - b(q_1 + q_2)$ is then random. It would be the choice of a consistent regulator, if firms were not risk averse. In our model, the regulator commits to a forward CO₂ price p or two prices, or organizes auctions.

Welfare gain from an optimized CCfD

To simplify the exposition of calculations we ignore asymmetric information. The effects related to asymmetric information are similar with all price instruments and do not influence the comparison between a myopic and an optimal CCfD.

A myopic CCfD would simply set a price equal to the expected CO₂ price $\hat{p} = B'(q_1 + q_2)$. With such a price, the resulting quantities $\hat{q}_1$ and $\hat{q}_2$ solve, with $\rho_i = \lambda \sigma_i^2$:

$$\begin{aligned} a - b(q_1 + q_2) &= \hat{p} = c_1 + \rho_1 + \beta_1 q_1 + \gamma q_2 \\ &= c_2 + \rho_2 + \beta_2 q_2 + \gamma q_1 \end{aligned}$$

Comparing these equations with the first-order conditions:

$$a - b(q_1^* + q_2^*) = c_1 + \beta_1 q_1^* + \gamma q_2^* = c_2 + \beta_2 q_2^* + \gamma q_1^*$$

This implies that:

$$\begin{aligned} (\beta_1 + b)(q_1^* - \hat{q}_1) + (\gamma + b)(q_2^* - \hat{q}_2) &= \rho_1 \\ (\beta_2 + b)(q_2^* - \hat{q}_2) + (\gamma + b)(q_1^* - \hat{q}_1) &= \rho_2 \end{aligned}$$

Rewriting the decomposition of welfare (13):

$$\hat{W} = W_P^S - \frac{1}{2} \left\{ (q_1^* - \hat{q}_1) \left[(\beta_1 + b)(q_1^* - \hat{q}_1) + (\gamma + b)(q_2^* - \hat{q}_2) \right] + (q_2^* - \hat{q}_2) \left[(\beta_2 + b)(q_2^* - \hat{q}_2) + (\gamma + b)(q_1^* - \hat{q}_1) \right] \right\}$$

Substituting the equations obtained above for the difference $(\hat{q}_i - q_i^*)$, the welfare loss is

$$\begin{aligned} W_P^S - \hat{W} &= \frac{1}{2} \left\{ (q_1^* - \hat{q}_1) \rho_1 + (q_2^* - \hat{q}_2) \rho_2 \right\} \\ &= \frac{1}{2} \frac{1}{(\beta_1 + b)(\beta_2 + b) - (\gamma + b)^2} \left\{ [(\beta_2 + b)\rho_1 - (\gamma + b)\rho_2] \rho_1 + [(\beta_1 + b)\rho_2 - (\gamma + b)\rho_1] \rho_2 \right\} \\ &= \frac{1}{2} \frac{1}{(\beta_1 + b)(\beta_2 + b) - (\gamma + b)^2} \left\{ (\beta_2 + b)\rho_1^2 + (\beta_1 + b)\rho_2^2 - 2(\gamma + b)\rho_1\rho_2 \right\} \end{aligned}$$

then, the difference between a uniform price and two prices is

$$W_P^S - W_P^N = \frac{1}{2} \frac{(\rho_1 - \rho_2)^2}{\beta_1 + \beta_2 - 2\gamma}$$

The difference between the two gives $W_P^N - \hat{W}$. Noting that

$$(\beta_1 + b)(\beta_2 + b) - (\gamma + b)^2 = \Delta + b(\beta_1 + \beta_2 - 2\gamma) = (\beta_1 + \beta_2 - 2\gamma)(\Gamma + b)$$

the difference is

$$\begin{aligned} W_P^N - \hat{W} &= \frac{1}{2} \frac{1}{(\beta_1 + \beta_2 - 2\gamma)(\Gamma + b)} \\ &\times [(\beta_2 + b)\rho_1^2 + (\beta_1 + b)\rho_2^2 - 2(\gamma + b)\rho_1\rho_2 - (\Gamma + b)(\rho_1 - \rho_2)^2] \end{aligned}$$

and the bracket term is equal to

$$\frac{[(\beta_1 - \gamma)\rho_2 + (\beta_2 - \gamma)\rho_1]^2}{\beta_1 + \beta_2 - 2\gamma}$$

which gives the equation in the main text.

C Micro-founded interpretation of supply responses

In the quadratic model, the supply response of technology 2 to its own price is

$$\frac{\partial q_2}{\partial p_2} = \frac{\beta_1}{\beta_1 \beta_2 - \gamma^2}.$$

The coefficient multiplying a shock to technology 2 is therefore governed by the slope of the alternative technology. This reduced-form coefficient captures how easily production can move toward technology 2 when its relative profitability changes.

This interpretation is useful for the price–quantity comparisons in Propositions 3 and 4. In the variability terms, the shock to technology 2 is weighted by coefficients involving β_1 , showing that this parameter affects the transmission of technology-2 cost shocks into quantity fluctuations.

The micro-founded model makes this mechanism explicit. An increase in p_2 expands blue-hydrogen adoption through two margins. First, it induces entry from the polluting technology along the blue-hydrogen adoption frontier. Second, it induces substitution from green to blue hydrogen along the technology-choice frontier. Formally:

$$\frac{\partial q_2}{\partial p_2} = \int_{c_1=p_1-\rho_1}^{+\infty} f(c_1, p_2 - \rho_2) dc_1 + \int_{c_2=0}^{p_2-\rho_2} f(c_2 + p_1 - p_2 + \rho_2 - \rho_1, c_2) dc_2.$$

By contrast, only the first margin affects total adoption, since switching from green to blue changes the technology mix but not aggregate decarbonization:

$$\frac{\partial q}{\partial p_2} = \int_{p_1-\rho_1}^{+\infty} f(c_1, p_2 - \rho_2) dc_1.$$

This term measures the density of sites located along the blue-hydrogen adoption frontier. It is therefore the micro-founded counterpart of the reduced-form coefficients that govern the transmission of technology-specific cost shocks into aggregate quantity variability.

D Sensitivity Analysis

D.1 Full numerical results

Table D.1 reports expected welfare under asymmetric information for the benchmark calibration and all sensitivity exercises. Table D.2 reports the corresponding welfare levels in the absence of asymmetric information. All values are expressed in billion euros.

Scenario	Naive	W_P^N	W_P^S	W_Q^N	W_Q^S	W_Q^+
Benchmark	9.47	21.19	21.79	21.25	21.16	22.84
Decarbonization target 40%	5.86	13.90	13.93	14.54	14.19	15.70
Decarbonization target 70%	13.89	28.78	29.88	28.41	28.45	30.19
Risk aversion $\lambda = 0.5$	16.72	21.77	21.79	22.43	21.16	22.84
Risk aversion $\lambda = 1.5$	4.71	20.07	21.79	19.61	21.16	22.84
Net elasticity $e \simeq 0.16$	21.76	50.23	50.25	54.52	54.42	56.10
Net elasticity $e \simeq 1.45$	5.43	11.67	12.82	10.33	10.23	11.92
Edge-concentrated density	7.83	19.66	19.96	19.69	18.55	21.04
Diagonal-concentrated density	19.26	27.33	28.01	27.50	26.53	29.17

Table D.1: Expected welfare under asymmetric information across instruments and calibration variants. Values are in billion euros.

Scenario	Naive	W_P^N	W_P^S	W_Q^N	W_Q^S	W_Q^+
Benchmark	7.10	19.44	21.16	19.44	21.16	21.16
Decarbonization target 40%	3.98	12.68	14.19	12.46	14.19	14.19
Decarbonization target 70%	11.73	26.52	28.45	26.52	28.45	28.45
Risk aversion $\lambda = 0.5$	12.10	20.68	21.16	20.67	21.16	21.16
Risk aversion $\lambda = 1.5$	1.58	17.38	21.16	17.02	21.16	21.16
Net elasticity $e \simeq 0.16$	17.68	52.70	54.42	52.70	54.42	54.42
Net elasticity $e \simeq 1.45$	3.62	8.51	10.23	8.51	10.23	10.23
Edge-concentrated density	3.22	18.12	18.55	17.76	18.55	18.55
Diagonal-concentrated density	16.88	24.63	26.53	24.16	26.53	26.53

Table D.2: Welfare in the absence of asymmetric information across instruments and calibration variants. Values are in billion euros.

Note: The benchmark calibration corresponds to a 55% decarbonization target, $\lambda = 1$, $e \simeq 0.5$, and the original spatial density. The associated duplicate rows are omitted.

D.2 Sensitivity to technology-specific cost shocks

Table D.3 examines how the gains from technology discrimination depend on the scale and composition of asymmetric-information shocks. The gain from discrimination under the neutral quota with targeted subsidies is relatively stable across specifications. By contrast, the gain from price discrimination increases as the scale of both shocks is reduced. The difference between the two discrimination gains is largely driven by the shock affecting technology 2: when θ_2 is shut down, the price-based and quantity-based gains become very close. This is consistent with the presence of a large mass of sites near the technology-2 adoption frontier, since technology-specific prices expose aggregate deployment more strongly to shocks affecting that technology.

Shock specification	$W_P^S - W_P^N$	$W_Q^+ - W_Q^N$	$Q \text{ gain} - P \text{ gain}$
Benchmark (θ_1, θ_2)	0.61	1.59	0.98
Both shocks divided by 2	0.99	1.80	0.81
Both shocks divided by 4	1.50	1.83	0.33
Both shocks divided by 8	1.73	1.84	0.11
$\theta_1 = 0$	0.50	1.68	1.18
$\theta_2 = 0$	1.95	1.79	-0.15

Table D.3: Welfare gains from technology discrimination under alternative assumptions on technology-specific cost shocks. Values are in billion euros.

D.3 Sensitivity analysis to the distribution of sites

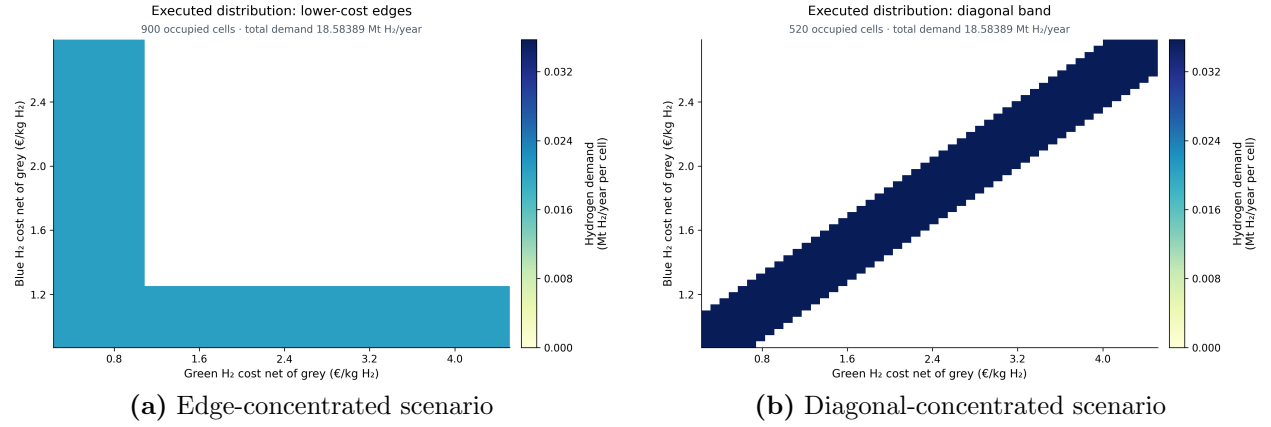


Figure D.1: Executed hydrogen-demand distributions over the cost grid in the two spatial sensitivity specifications. Total demand is distributed uniformly over thick supports near the lower-cost edges (a) or the diagonal in grid coordinates (b); these sensitivity matrices use no Gaussian filtering.