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GREEN WASTE

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ABSTRACT

We test for and measure green waste: the misallocation of public subsidies for green investment projects. Our context is a major Norwegian program for green investment subsidies. We develop a model of subsidy allocation and apply it to detailed project-level data on carbon emissions and subsidy amounts for both marginal and inframarginal projects. We find that decision-makers could have achieved the same level of emission reductions at less than half the cost. To isolate the sources of this green waste, we use data on both ex-ante expected and ex-post realized emission reductions for each project. We find that decision-makers are able ex-ante to identify the projects with the highest ex-post emission reductions but unwilling to select them.

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I. Introduction

Governments worldwide use targeted investment subsidies to speed the adoption of green technologies and cut carbon emission. A growing theoretical literature seeks to justify such subsidies as part of a second-best policy response (e.g., Acemoglu et al., 2012; Kotchen and Maggi, 2025). However, these theories assume that decision-makers are both able and willing to allocate green investment subsidies efficiently across firms and projects. But are they? Or are such subsidies green waste? And if so, how large is the misallocation and what are its sources?

Our goal is to answer these questions. The context of our study is Norway over the period 2012–2023. This context allows us to address key measurement challenges through access to a detailed administrative data set from the country's main program for green investment subsidies, which records project-level carbon emission reductions and subsidy amounts for both marginal and inframarginal investment projects. Combining these data with a model of subsidy allocation allows us to test for and measure misallocation. We find that decision-makers could have achieved the same level of carbon emission reductions at less than half the cost. To isolate the sources of this green waste, we use data on both ex-ante expected and ex-post realized carbon emission reductions for each project. We find that decision-makers are able ex-ante to identify the projects with the highest ex-post carbon emission reductions but unwilling to select them.

As explained in Section II, our analysis is made possible by several strengths of the Norwegian context and data. We study Enova, the main public program for green investment subsidies. A key advantage of this context is that both the program's objective and its subsidy allocation rule are known.[1] Enova's mandated objective is to reduce carbon emissions in private firms. This objective is pursued by allocating investment subsidies across so-called program areas targeting the adoption and use of specific green technologies. Within each program area, applications are ranked by their

[1] Knowing the decision-maker's mandated objective is critical to credibly measure misallocation, as emphasized by Canay et al. (2023). Otherwise, it becomes difficult to determine the optimal allocation, which makes it infeasible to draw conclusions about bias or misallocation of the actual allocation.

expected emission reductions per subsidy cost, and subsidies are awarded sequentially until the program's budget is exhausted. Combined with data on the ex-ante expected and ex-post realized emission effects for all funded projects, the allocation rule allows us to identify the marginal and inframarginal projects within each program and their corresponding emission outcomes.

In Section III, we present a model that formalizes how the institutional context and data can be used to test for and measure misallocation of green investment subsidies. We consider a decision-maker who can achieve emission reductions by allocating a fixed climate budget across Enova's program areas or to an alternative green policy. We allow for the possibility that the decision-maker's allocation is distorted because she has preferences over program areas that extend beyond their impact on carbon emissions. For example, certain programs may be systematically favored because they are popular among politicians or expected to benefit certain regions or interest groups.[2] The model also allows the decision-maker to have imperfect foresight regarding the eventual emission impacts of funded projects. As a result, the decision-maker may fund projects with inferior realized emission reductions because she has motives beyond emission reductions, is unable ex-ante to identify the projects with the highest ex-post emission reductions, or both.

To test for and measure misallocation, we begin by comparing the actual allocation with a counterfactual first-best allocation in which the decision-maker has no motives beyond emission reductions and full knowledge of ex-post emissions. This counterfactual allocation simply funds the projects with the highest ex-post emission reductions, equalizing marginal emission outcomes across Enova's programs and the alternative green policy. In contrast, the actual allocation may be distorted, failing to equalize marginal emission outcomes. Our measure of total misallocation is the difference in emission reductions achieved under the actual and first-best allocations.

To isolate the sources of misallocation, we next define a counterfactual second-best allocation

[2]While outright corruption (e.g., Shleifer and Vishny, 1993) seems implausible in our context, work in public administration emphasizes that civil servants may pursue their own self-interest due to agency problems (Wilson, 1989), particularly in settings like ours with limited oversight and few incentives to align the interests of the decision-makers with the principal's stated objectives.

in which the decision-maker has no motives beyond carbon emission reductions but selects projects based on ex-ante expected emission reductions. This allocation funds the projects with the highest *expected* emission reductions, equalizing expected marginal emission reductions across programs and policies. Using the second-best allocation, we decompose our measure of misallocation into two parts: One that arises because the decision-maker may have other motives than carbon emission reductions, and one that arises because the decision-maker selects projects based on ex-ante expected emission reductions that may differ from the ex-post realized ones.

In Section IV, we explain how we implement the tests and measures of misallocation given the model described in Section III and the data discussed in Section II. To test for misallocation, it follows from the model that we need data on realized carbon emission reductions for marginally accepted Enova projects as well as the emission reduction that could have been achieved under an alternative green policy. In the data, we observe Enova's expectations about the emission reductions of each funded project, as well as the ex-post realized emission reductions. These data allow us to identify the marginally accepted projects in the decision-maker's actual allocation and their corresponding emission outcomes. As the alternative green policy, we consider the purchase and deletion of emission quotas from the EU Emissions Trading System (EU ETS); in robustness analyses, we also present estimates based on other alternative green policies.[3]

While it is straightforward to test for misallocation given our data, it is more challenging to quantify its total magnitude. The main data challenge is that it is not possible to observe the emission reductions of *rejected* Enova projects. In Section IV.B, we address this challenge and show that total misallocation can be expressed as the sum of forgone emission reductions from rejecting Enova projects whose emission reductions exceed those of the alternative policy (Type I error) and from accepting Enova projects whose emission reductions fall below those of the alternative policy (Type II error). Because the former is unobserved but weakly positive, and the latter is directly

[3]Germany implemented this policy in 2023 when it voluntarily canceled emission quotas after closing two coal-fired electricity generators (European Commission, 2024). The EU ETS is the largest cap-and-trade program in the world and has been extensively studied in economics and finance (e.g., Akey et al., 2024; Martinsson et al., 2024).

observed in the data, this decomposition allows us to construct bounds on misallocation under weak or no assumptions. Point identification is also possible by following Cingano et al. (2025) and extrapolating outcomes from marginally accepted to rejected Enova projects.

In Section V, we present four sets of main results on misallocation. The first is concerned with *testing* for misallocation. We find substantial dispersion in marginal emission reductions across Enova's programs and strongly reject the null of equalized marginal reductions. A large majority of Enova programs have marginal emission reductions below those achievable in the alternative green policy; we can strongly reject that Enova's marginal reductions are equal to those of the alternative policy, suggesting pervasive misallocation at least on the margin.

The next set of results concerns *measuring* misallocation. We start by constructing a worst-case lower bound on total misallocation. Our lower bound corresponds to the loss in emission reductions from accepting Enova projects whose emission reductions fall below those of the alternative policy. We find that by optimally reallocating funds across Enova's programs and the alternative policy, the decision-maker could have increased emission reductions by at least 0.051 tons of CO_2 per Euro, equivalent to 91% of the average on accepted Enova projects. Put differently, Enova could have achieved the current level of emission reductions at less than half the cost. We also report point estimates and upper bounds. The point estimate is 0.052 tons of CO_2 per Euro while the upper bound is 0.090 tons of CO_2 per Euro, both consistent with substantial misallocation.

The third set of results concerns the *sources* of misallocation. We decompose our measures of misallocation into parts driven by the decision-maker's non-emission motives and by errors in predicting projects' eventual impact on carbon emissions. This is possible because we observe both ex-ante expected and ex-post realized emission effects for all funded projects. We find that misallocation is driven chiefly by the decision-maker's non-emission motives, while prediction errors play only a minor role. This suggests that the decision-maker is able ex-ante to identify the projects with the highest ex-post carbon emission reductions but unwilling to select them.

The final set of results concerns the *margins* of misallocation. We decompose our measures

of misallocation into an overspending margin on Enova relative to the alternative policy and a misspending margin across programs within Enova. We find that the most important margin for reducing misallocation is to reduce spending on Enova relative to the alternative policy. However, misallocation within Enova is also non-negligible. By optimally reallocating funds across Enova's programs, the decision-maker could significantly increase emission reductions. Further decomposing the overspending and misspending components, we find that non-emission motives are the primary driver at both margins. This finding suggests that errors in predicting emission reductions play only a minor role in explaining misallocation, both across Enova's programs and between Enova and the alternative policy.

In Section VI, we offer concluding remarks and discuss the implications of our findings for policymakers and researchers. We argue the problem of misallocation can be addressed by setting a common minimum rate of return that all caseworkers need to expect from an investment. The minimum return should reflect the opportunity cost of the funds, such as the payoff to an alternative green policy. We also argue that our paper offers a blueprint for researchers to empirically analyze misallocation of government subsidies. We show the importance of focusing on marginal, rather than average, returns when testing for misallocation, and the need for inframarginal returns to measure misallocation. We also show how to construct informative bounds on misallocation in settings where point identification is not feasible.

Our research connects to several literatures. First, a comprehensive body of empirical work reports the mean impacts of environmental policies, documenting substantial variation in average emission reductions per subsidy cost across programs (e.g., Hoppe et al., 2023; Hahn et al., 2024; see Gillingham and Stock, 2018 for a review).[4] However, as explained by Heckman et al. (1998) and Canay et al. (2023), average outcomes are generally uninformative about marginal ones, which are necessary to test for misallocation. Moreover, to quantify misallocation, it is necessary to point-

[4] A large literature evaluates the effect of specific environmental subsidies, such as for EVs (e.g., Jacobsen et al., 2023; Allcott et al., 2024; Bena et al., 2025), energy efficiency programs (e.g., Allcott and Greenstone, 2012; Fowlie et al., 2018), and solar power (e.g., Gerarden, 2023). We study misallocation of public funds across green technologies.

identify or bound the individual effects of both marginal and inframarginal (accepted and rejected) projects. Using data on emission effects for both marginal and inframarginal projects, we provide new evidence on the extent and the sources of misallocation of green investment subsidies.

A second literature that we relate to studies the misallocation of capital across firms, reviewed by Syverson (2011). This work documents substantial dispersion in revenue-to-input ratios — measures of average products — across establishments within narrow industries in the United States and elsewhere. However, as emphasized by Bils et al. (2021), such dispersion reflects misallocation only when marginal and average products align and when products are measured without error. In our context, we can directly identify marginal and inframarginal investment projects and exploit administrative data to accurately measure their emission outcomes.

A third literature that we relate to examines the availability of financing for green projects and, more broadly, how financial markets price climate risk (e.g., Giglio et al., 2021; Baker et al., 2022). An emerging strand of this literature questions whether financing tools for climate projects, such as green bonds, actually induce additional green investments or instead compensate firms for activities they would have undertaken anyway (e.g., Lam and Wurgler, 2024).[5] We provide evidence that green investment subsidies can raise firms' investments in projects that reduce carbon emissions.[6] However, the total carbon emission reductions achieved by these investment subsidies could be substantially higher if the most effective projects were systematically selected.

Finally, we connect to ongoing policy debates in the United States and Europe. A key takeaway from our results is that the effectiveness of discretionary climate policies can be severely undermined by decision-makers' non-emission motives. This may lead to misallocation even in settings where mandated policy objectives are simple and clear, and decision-makers can accurately predict the eventual impact of climate projects on emissions. By reallocating funds, decision-makers could

[5] A related literature shows that firms may overstate their environmental efforts to bolster their reputations, often referred to as greenwashing (e.g., He et al., 2024; see Griffin and Kruger (2024) for a survey).

[6] Thus, we also connect to a broader literature that studies firms' responses to carbon taxes and cap-and-trade systems, including Bartram et al. (2022), Brown et al. (2022), and Martinsson et al. (2024).

achieve substantially higher carbon emission reductions per subsidy cost. If they want to.

II. Institutional Background and Data

We now describe the institutional context and provide an overview of the data.

A. Institutional context

Context. Norway is a small open economy with a GDP per capita comparable to that of the U.S.[7] Under the Paris Agreement, Norway has promised to reduce its carbon emissions by 50% by 2030 relative to 1990 levels. Its climate policy is closely linked to that of the European Union (EU), both through the European Economic Area Agreement and through cooperation to meet the Paris Agreement's 2030 climate targets. Norway also participates in the EU Emissions Trading System, a carbon emission trading scheme launched in 2005 to reduce emissions across the EU.

To achieve its climate goals, the Norwegian government employs a mix of direct carbon emission taxation, emission quotas, and subsidies for firm investments in low-emission technologies, such as electric heavy machinery, solar panels, and central heating systems. The vast majority of these green investment subsidies are distributed through Enova, a state-owned enterprise tasked with promoting carbon emission reductions among Norwegian firms. Over the period 2012–2023, Enova awarded NOK 30.3 billion in subsidies to 7,754 firms across 22,260 projects.[8] Little, if anything, is known about the allocative efficiency of these green investment subsidies.

We next describe the four-step subsidy process of Enova, illustrated in Figure 1. In the course of doing so, we also introduce some notation that will be useful both in the economic model in Section III and the econometric analysis in Sections IV–V.

[7] We refer to Mogstad et al. (2025) for a description of the Norwegian economy and a comparison to other OECD countries.

[8] With a population of about 5.6 million, NOK 30.3 billion amounts to NOK 5,400 (USD 545) per capita.

Step 1: Application. Firms apply for Enova subsidies by offering carbon emission reductions through green investments. Applications are sent to so-called program areas, which define categories of green investments eligible for subsidy. The program areas are grouped by Enova into seven broad topics: Biogas and biofuel, energy systems and heating, manufacturing, construction and real estate, infrastructure, technology development, land transportation, and maritime transportation. Appendix Table A.I lists the program areas within each topic. In 2022, there were 38 programs. For example, a firm investing in a geothermal heating pump would send its application to the program "*Heating Plants*," while a firm investing in a new electric fishing boat would send it to "*Electrification of Maritime Transport*," a separate program. However, all programs share the same key objective — to maximize carbon emission reductions for a given budget.

In the application, each firm specifies the green investment it seeks to make along with the anticipated carbon emission effect, Δ^A, from undertaking the investment. For example, a firm seeking to invest in a geothermal heating pump may report that the investment will reduce its carbon emissions by $\Delta^A = 100$ tons of CO_2 relative to a counterfactual without the investment. To substantiate Δ^A, the firm must report detailed information on expected investment and energy consumption over the project's lifetime. The firm must also provide information about likely investments and emissions for a counterfactual scenario without the subsidy.

Firms do not specify a subsidy amount in their applications. Instead, the subsidy amount, denoted by c, is determined by the type of green investment being made, in accordance with EU regulations on state aid. Since different programs target different types of investments, subsidy rates vary across programs, covering 20–50% of the firm's total investment costs.

Step 2: Evaluation. Applications are evaluated on a program-by-program basis. For each project, a caseworker forms her own expectation of the carbon emission effect from undertaking the stated green investment, $\mathcal{E}(\Delta)$. To do so, the caseworker must assess the firm's expected investment and resulting carbon emissions both with and without the subsidy.

To assess the likely carbon emissions with the subsidy, the caseworker reviews reported infor-

mation on expected investment and energy consumption over the project's lifetime, and validates (or reassesses) these figures using independent sources on the energy use of different green technologies. To assess the likely carbon emissions without the subsidy, it is critical to gauge the extent to which the subsidy generates additionality in investment. The caseworker therefore reviews reported project-level information on expected cash flows and the applicant's cost of capital. This allows the caseworker to make informed predictions about whether the stated investment would have been undertaken even without a subsidy, in which case the subsidy would generate no investment additionality and, therefore, no impact on emissions. For example, while a firm investing in a geothermal heating pump may state an emission effect of $\Delta^A = 100$ tons of CO_2, Enova may expect the same investment to reduce carbon emissions by only $\mathcal{E}(\Delta) = 75$ tons of CO_2 — either because the firm understates emissions with the investment, overstates emissions without the investment, or both.

Step 3: Allocation. Within each program, applications are ranked by the expected carbon emission effect per subsidy cost, $\frac{\mathcal{E}(\Delta)}{c}$, and subsidies are then assigned in order. As illustrated in Figure 1, the highest-ranked application receives a subsidy first; the next-highest receives one if funds remain, and so on. This process continues until the program's budget is exhausted, creating a cutoff rank q_r^c in the distribution of applications for program r. Applications ranked above this cutoff are awarded a subsidy ($D = 1$), while those ranked below are rejected ($D = 0$).

It is useful to observe that the $\frac{\mathcal{E}(\Delta)}{c}$ of the marginal application at q_r^c may vary across programs for two reasons. The first is that some programs may attract applications with higher $\frac{\mathcal{E}(\Delta)}{c}$. For example, in Figure 1, it could be that $\frac{\mathcal{E}(\Delta)}{c}$ differs between the marginal firm in Program 2 (Firm 6) and the marginal firm in Program 3 (Firm 9), even if both programs receive the same funding and accepted the same number of applications. The other reason is that some programs may receive less funding than others. For example, it could be that Program 1 accepts only one application (Firm 3) because it has very limited funding, but this application has a higher $\frac{\mathcal{E}(\Delta)}{c}$ than the marginal applications in other programs that accept more applications because they receive higher

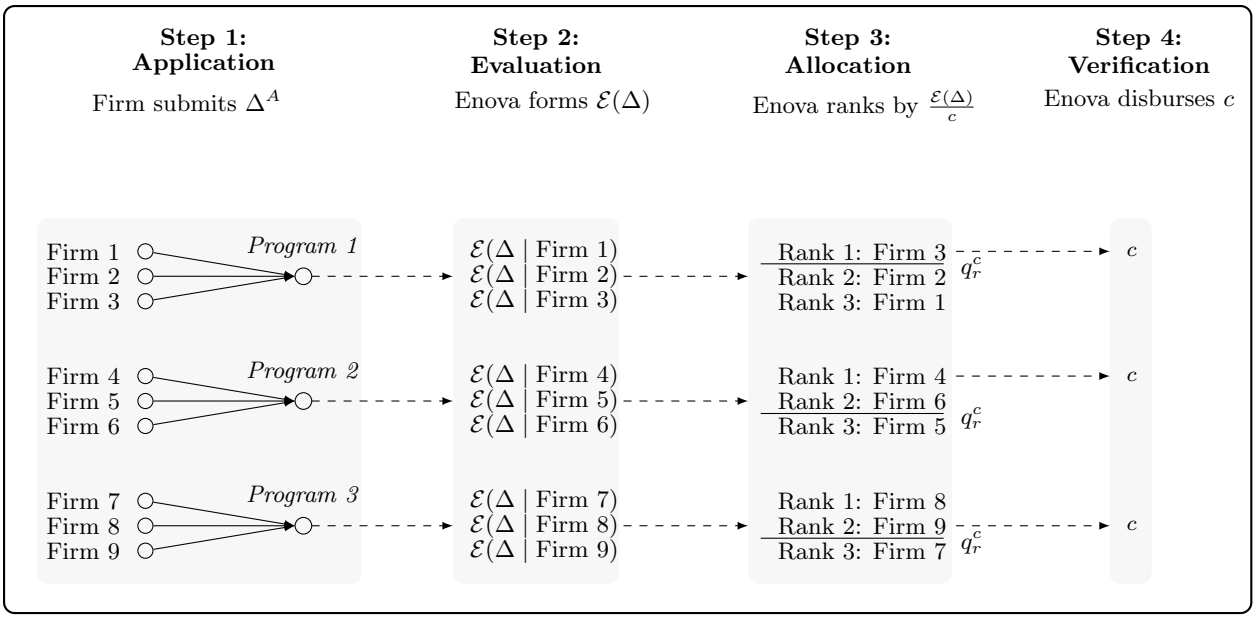


Figure 1. A three-program illustration of the steps in the Enova subsidy process.

funding.

Regardless of program area, the legal obligations of subsidy winners ($D = 1$) remain the same. When a subsidy is awarded, the firm and Enova enter into a contract in which the firm receives the subsidy amount c conditional on making the specified green investment.

Step 4: Verification. After a project is completed, subsidy winners must submit a final report detailing the green investment. Winners are required to share receipts and project performance measures for up to ten years after completion. Enova disburses the subsidy amount c only *after* verifying that the contracted green investment has been made. At this stage, Enova also assesses the realized carbon emission effect of the project, denoted by Δ, which may differ from both the stated (Δ^A) and expected ($\mathcal{E}(\Delta)$) effects. For example, a geothermal heating pump may prove less effective than both stated and expected — due to downtime or lower-than-anticipated efficiency — and reduce the subsidy winner's carbon emissions by only $\Delta = 50$ tons of CO_2. These verifications are carried out by Enova caseworkers or, in some cases, independent third-party experts.

B. *Data and institutional information*

Our paper combines three sources of data:

Enova data. We use a new data set on Enova subsidies covering all project applications submitted between 2012 and 2023. Our sample comprises 20,699 applications from 7,154 unique firms processed during this period.[9] Each application contains complete information on the firm's anticipated carbon emission effect Δ^A, and all accepted applications contain complete information on Enova's expected effect, $\mathcal{E}(\Delta)$, and the ex-post realized effect, Δ.[10] For each application, we also observe the proposed green investment, the corresponding program area r, the firm's tax identification number, the project duration, and the amounts of funding requested and awarded.

Firm data. We link the Enova subsidy data to firm-level administrative records from Statistics Norway. These data cover the universe of limited liability firms, the most common legal form in Norway, and include detailed information on firm-level output (e.g., revenues), inputs (e.g., capital, labor, and intermediates), industry classification codes, and geographical identifiers. See Akerman et al. (2015) and Hvide and Meling (2023) for more details on these databases.

Institutional information. As discussed in Section II, Enova ranks applications by the expected carbon emission reduction per subsidy cost. In most program areas, Enova is instructed to only consider the direct reduction in carbon emission that occurs in the firm that applies for the subsidy. The Enova measures $\mathcal{E}(\Delta)$ and Δ allow us to observe these quantities.

However, for a subset of program areas, caseworkers are also instructed to consider carbon emission reductions from possible spillover effects on other firms.[11] Such spillovers are neither

[9] For our main misallocation measures defined in Section III, we require data on both expected ($\mathcal{E}(\Delta)$) and realized (Δ) emission effects. We have therefore excluded a small number of projects with missing $\mathcal{E}(\Delta)$, and a larger number of projects that are still in process by 2023 (the last year of our sample period) as these lack a recorded Δ.

[10] All carbon emission effects are reported in present value terms using a 2% annual discount rate. Appendix Table A.III presents misallocation estimates using alternative discount rates ranging from 0% to 6%.

[11] Note that for this set of programs, caseworkers are only allowed to consider direct and indirect *carbon emission*

quantified in the applications nor in the caseworker's expectations. As a result, we do not have information about the existence or magnitude of spillover effects.

To address this issue, we hand-collect historical data from each program area's funding calls on how much weight, if any, caseworkers are instructed to place on possible spillovers relative to direct emission effects. These data show that caseworkers are instructed to consider possible spillovers in a subset of programs, accounting for about 10% of our sample of applications. In the remaining programs, project rankings are based solely on direct emission effects, as captured by $\mathcal{E}(\Delta)$. In Section V.G, we present a robustness analysis that restricts the sample to these programs, along with a bounding exercise that clarifies the potential confounding effect of unmeasured spillover effects.

C. Summary statistics

In Table I, we present descriptive statistics from the full estimation sample.

Project characteristics. Panel A of Table I summarizes project characteristics. About 65% of applications are accepted, with an average subsidy amount, c, of about EUR 131,000, covering 46% of the project's total cost. On average, firms state in their applications that the project will reduce carbon emissions by $\frac{\Delta^A}{c} = 0.22$ tons of CO_2 per subsidy EUR, while Enova expects a reduction of $\frac{\mathcal{E}(\Delta)}{c} = 0.10$ tons of CO_2 per subsidy EUR.[12]

Applicant characteristics. Panel B of Table I summarizes applicant firm characteristics. The average applicant firm that receives investment subsidies is about 19 years old, generates EUR 6.3

effects. Other possible effects *unrelated* to carbon emission reductions, such as job creation, are outside its mandate and should not be used to determine how projects are ranked.

[12] While the average values of $\frac{\mathcal{E}(\Delta)}{c}$ and $\frac{\Delta}{c}$ are close, at 0.10 and 0.08 tons of CO_2 per subsidy EUR respectively, these averages mask substantial variation across projects. For 78% of projects, Enova either underestimates ($\frac{\mathcal{E}(\Delta)}{c} < \frac{\Delta}{c}$) or overestimates ($\frac{\mathcal{E}(\Delta)}{c} > \frac{\Delta}{c}$) the eventual carbon emission effect, with an average gap of 29%, indicating meaningful prediction errors. For the remaining 22% of projects, the expected and realized carbon emission effects coincide.

Table I. Summary Statistics

	Accepted		**Rejected**	
	Mean	*Std.dev*	*Mean*	*Std.dev*
Panel A: Project characteristics				
Subsidy amount in EUR 1000 (c)	131.30	2128.75	362.35	3150.14
Stated carbon emission effect (Δ^A/c)	0.22	0.84	0.09	0.35
Expected carbon emission effect ($\mathcal{E}(\Delta)/c$)	0.10	0.12	-	-
Realized carbon emission effect (Δ/c)	0.08	0.12	-	-
Investment cost share (%)	46.42	1.78	46.10	1.83
Project completion time (months)	7.42	10.56	-	-
Number of projects	13,493		7,206	
	Accepted		**Rejected**	
	Mean	*Std.dev*	*Mean*	*Std.dev*
Panel B: Firm characteristics				
Firm age	18.9	14.4	16.1	13.4
Employees	87.3	270.5	77.9	263.2
Sales	6.3	7.3	5.2	6.8
Wage cost	1.3	1.5	1.2	1.4
Capital cost	0.2	0.3	0.2	0.3
Materials cost	3.1	4.0	2.4	3.6
Number of firms	4,502		3,882	

Notes: Panel A presents summary statistics for our sample of accepted and rejected subsidy applications. Carbon emission effects are measured in tons of CO_2 per subsidy EUR. Δ^A is observed for all applications, while $\mathcal{E}(\Delta)$ and Δ are observed only for accepted projects. The investment cost share is the share of the firm's total investment cost covered by the Enova subsidy. Completion time is defined as the duration between the subsidy decision date and the date the project receives its final payment. Panel B presents summary statistics for the applicant firms. Financial variables are reported in EUR 2015 million, and winsorized at the 1st and 99th percentiles.

million in sales, and employs 87 people. Compared to the broader population of Norwegian firms, the firms in our sample are older and larger. Applicant firms that receive investment subsidies from Enova are on average slightly older and larger than those that apply but are rejected.

D. Descriptive evidence: Winning a subsidy

In Section III, we specify the decision-maker's problem and analyze the misallocation of green investment subsidies relative to an optimal allocation rule. Before turning to that analysis, we first use our Enova and firm data to describe what it means to win an Enova subsidy.

To do so, we estimate regressions comparing firms, indexed by j, that are first-time Enova subsidy winners in year t ($D_{jt} = 1$) to firms that apply in year t but lose ($D_{jt} = 0$), before and after the application. Let e denote an event time relative to t, and let y_{jt+e} denote an outcome variable for firm j. For each event time $e = -3, \ldots, 4$, our baseline regression model is:

$$y_{jt+e} = \sum_{e' \neq \bar{e}} \mathbf{1}_{e'=e} \mu_{te'} + \sum_{j'} \mathbf{1}_{j'=j} \psi_{j't} + \sum_{e' \neq \bar{e}} \mathbf{1}_{e'=e} D_{jt} \lambda_{te'} + \varepsilon_{jte}, \tag{1}$$

where λ_{te} is the change in the outcome for winners of a subsidy relative to the control group for a particular pair (e, t) and $\bar{e} = -2$ is the omitted event time. The inclusion of firm fixed effects in equation (1) controls for any time-invariant differences between winners and losers of Enova subsidies — for example, fixed differences in productivity — while the inclusion of event time fixed effects controls for any common shocks experienced by all firms during the time interval.[13]

Outcomes from the Enova data. The first set of outcome variables we consider comprises the win probability and value of current and future Enova subsidies. These outcomes, presented in Figure 2, allow us to describe the treatment associated with winning an Enova subsidy.

[13] We restrict the estimation sample to first-time winners and losers that applied before 2020, so that all firms can be followed for at least four years after the subsidy decision. Accordingly, the estimates in this section are based on a slightly smaller sample of firms than the summary statistics in Table I, which use all project applications.

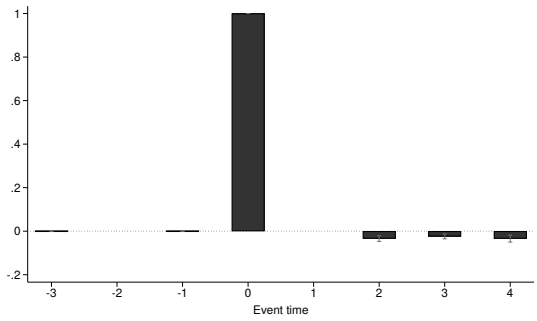
Panel A shows the share of firms that are first-time subsidy winners. Mechanically, both treated and control units have no wins prior to $e = 0$, so the effect is zero for $e < 0$. At $e = 0$, treated firms win a subsidy for the first time, while control firms apply but do not win, which means the effect equals one by construction. For $e > 0$, the estimates can be small or large depending on how a first subsidy win at $e = 0$ affects the probability of winning again in future years. Panel B of Figure 2 shows the share of firms that win a subsidy in a given relative year, e. The results show that future subsidy wins are only weakly correlated with past ones: A firm that is currently awarded a subsidy is not much more likely to win a subsidy in the future. This suggests we can infer lagged responses to a subsidy win by regressing outcomes measured in years $e > 0$ on winning in year $e = 0$.

As explained in Section II.A, subsidies are disbursed only after Enova verifies that the contracted green investment has been made. In Panel C of Figure 2, the black line shows mean verified investments among subsidy winners. At $e = 0$, the mean verified investment is around EUR 160,000; by $e = 4$, it reaches around EUR 370,000. This is almost identical to the amount of investment promised in the contract at $e = 0$, shown in blue. This reflects that the vast majority of projects are completed and verified by $e = 4$.[14] Since Enova covers no more than 50% of the investment costs, subsidy payments are lower than verified investments, as shown by the green line in Panel C.

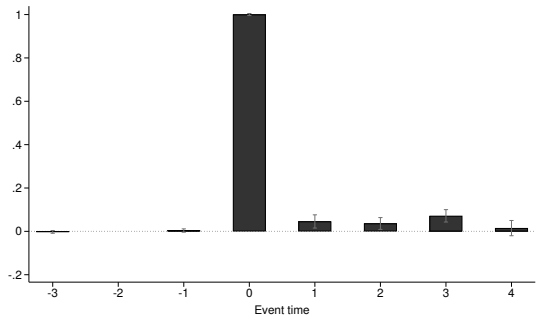
Outcomes from the firm data. The next outcome variable we consider is the firm's total investments. Panel C of Figure 2 shows that subsidy winners, on average, increase their verified green investments by nearly the exact amount promised in their contracts with Enova. However, Enova only verifies green investments related to the accepted projects. It is possible that subsidy winners would have invested even in the absence of a subsidy, in which case the actual investment response would be smaller than suggested by the estimates in Panel C of Figure 2.

We measure the firms' cumulative investments as the change in total fixed tangible assets relative

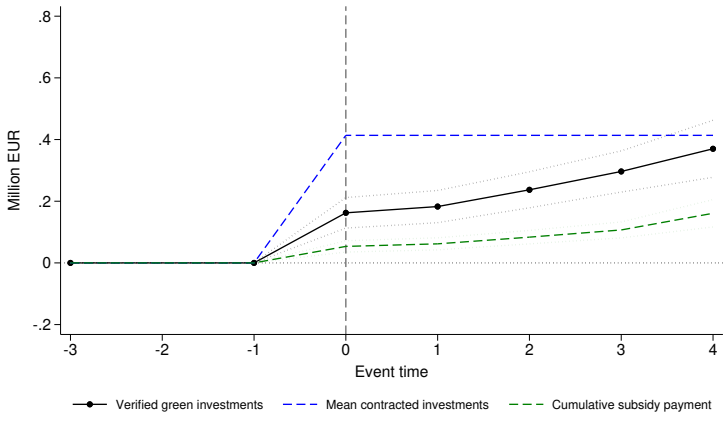
[14] In Appendix Figure A.1, we plot the share of projects that are completed over event time. By event time $e = 2$, 94% of projects are completed; by $e = 5$, the share increases to 98%.



Panel A: Indicator for first-time win



Panel B: Indicator for any win



Panel C: Contracted and verified investment

Figure 2. Visualizing the research design. This figure presents estimates from equation (1) of the impacts of winning an Enova subsidy. The omitted event time is $e = -2$. The outcomes considered are: the probability of winning an Enova subsidy for the first time (Panel A), the probability of winning an Enova subsidy in the current year (Panel B), and the cumulative value of green investments verified by Enova (Panel C). In Panel C, the blue dashed line shows the mean contracted investment among first-time winners at $e = 0$, while the green dashed line shows the cumulative value of subsidy payments to the firm, reported separately by event year. Shaded areas represent 95% confidence intervals. Specification details and sample definitions are provided in the main text.

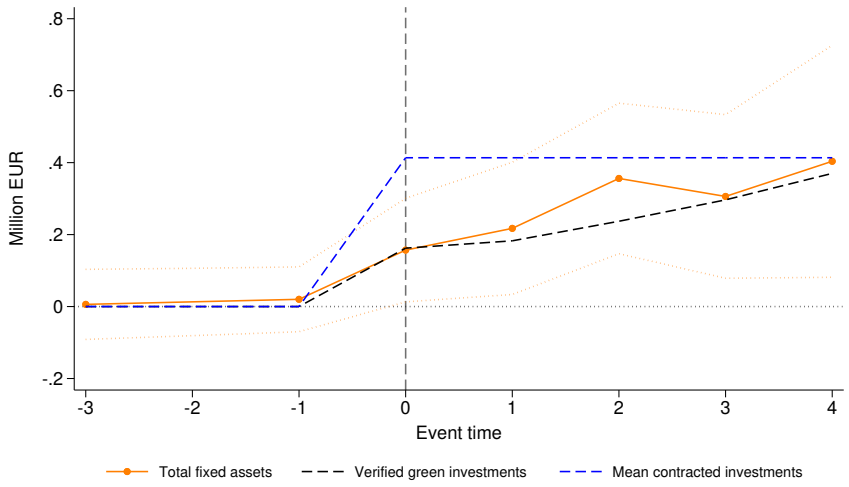


Figure 3. Average investment response. The figure presents estimates from equation (1) of the impact of winning an Enova subsidy. The omitted event time is $e = -2$. The outcome is the firm's fixed tangible assets. Estimated effects are shown in orange, with shaded areas representing 95% confidence intervals. The blue line shows the mean contracted investment among first-time winners at $e = 0$; the black line shows the cumulative value of green investments verified by Enova. Specification details and sample definitions are provided in the main text.

to the omitted event time $e = -2$, using the balance sheet data described in Section II.B. Figure 3 presents estimates from equation (1) with total fixed tangible assets as the outcome variable. At $e = 0$, subsidy winners increase their fixed assets by EUR 157,000 relative to losers; by $e = 4$, the increase reaches EUR 404,000. The estimated investment response is nearly identical to the verified green investment reported in Panel C of Figure 2, suggesting that winning an Enova subsidy neither crowds out nor crowds in other investments.

The last set of outcomes we consider lets us study how firms adjust their use of other inputs and their output after winning an Enova subsidy. We estimate equation (1) with firm-level revenue, labor costs, and intermediate inputs as outcomes. In Table II, we find that subsidy winners increase revenue and intermediate inputs by 8% and 11%, respectively, with no significant change in total labor cost. This is consistent with intermediates being complementary to capital. Row (6) of Table II shows that the increase in output is fully accounted for by higher input use, rather than by a shift in productivity. Similarly, row (4) shows no significant evidence that winners increase

their R&D intensity, as measured (imperfectly) by the stock of intangible assets.

Table II. Firm Outcomes

		Years after treatment					
	Pre (pooled)	$e = 0$	$e = 1$	$e = 2$	$e = 3$	$e = 4$	Post (pooled)
				Panel A: Inputs			
Log fixed tangible assets	-0.01	0.08	0.18	0.18	0.19	0.14	0.18
	(0.023)	(0.048)	(0.054)	(0.061)	(0.065)	(0.085)	(0.057)
Log materials	0.03	0.04	0.01	0.08	0.13	0.29	0.11
	(0.040)	(0.067)	(0.070)	(0.077)	(0.078)	(0.121)	(0.069)
Log labor cost	-0.02	-0.02	-0.04	-0.04	-0.05	-0.02	-0.04
	(0.026)	(0.040)	(0.049)	(0.055)	(0.054)	(0.074)	(0.046)
Log fixed intangible assets	0.01	0.04	0.03	-0.01	-0.05	-0.01	-0.01
	(0.059)	(0.095)	(0.123)	(0.124)	(0.131)	(0.181)	(0.114)
				Panel B: Output			
Log of sales	0.04	-0.02	0.07	0.07	0.08	0.09	0.08
	(0.027)	(0.044)	(0.054)	(0.058)	(0.062)	(0.085)	(0.052)
Log sales - Predicted log sales (OLS)	-0.05	-0.07	0.04	-0.00	-0.05	-0.02	-0.01
	(0.041)	(0.058)	(0.067)	(0.075)	(0.076)	(0.106)	(0.067)
Log sales - Predicted log sales (LP)	-0.01	-0.06	0.02	-0.02	-0.05	-0.02	-0.02
	(0.030)	(0.043)	(0.049)	(0.053)	(0.056)	(0.082)	(0.049)
Number of firms	1484	1484	1484	1484	1484	1484	1484

Notes: The table presents estimates from equation (1) of the impacts of winning an Enova subsidy. The omitted event time is $e = -2$. All variables from firms' income statements and balance sheets are reported in fixed 2015 prices and subsequently log-transformed. Predicted log sales is calculated as follows: Using pre-treatment data only, we first estimate the output elasticities of log capital, log labor cost, and log materials, separately using OLS and the approach of Levinsohn and Petrin (2003). We then predict log sales by multiplying the estimated output elasticities by the subsidy-induced increase in inputs. Standard errors are reported in parentheses.

Investment additionality and misallocation. Overall, the evidence shows that subsidy winners, on average, increase their verified green capital and total capital stock by nearly the exact amount promised in their applications to Enova. If the promised investment would have been undertaken even without a subsidy, the subsidy would generate no investment additionality and, therefore, no impact on emissions. By contrast, the evidence above suggests full investment additionality: Winning a subsidy induces the firm to undertake a green investment it otherwise would not have made.

It is useful to observe that our conclusion of substantial misallocation in our paper does not

depend on the degree of investment additionality. Importantly, the lower bound on misallocation that we derive is valid regardless of whether it is full, no, or some investment additionality. As shown in Appendix I.G, the bound will contain the truth even if the firm would have undertaken, all, or some of the promised investment even without a subsidy, in which case the subsidy could have no or little impact on carbon emission. However, the tests for and point estimates of misallocation assume full investment additionality, as suggested by the data.

While Enova appears able to induce additional green investment, this does not imply that its subsidies are allocated efficiently. Misallocation can arise if spending is not optimally distributed across Enova's program areas and alternative green policies. For example, Enova may overspend on politically favored programs that deliver low emission reductions per subsidy cost compared to other Enova programs or to alternative green policies. In our context, spending more on one program area lowers that area's cutoff rank q_r^c, allowing more projects to be funded there, but at the expense of fewer projects being funded in other programs or policies, as illustrated in Section II.A.

III. Measuring Misallocation

We now present a model in which a decision-maker allocates climate funds across Enova's program areas and an alternative green policy. The purpose of the model is to guide our empirical analysis testing for and measuring the misallocation of green investment subsidies.

A. Notation

We consider a decision-maker who can achieve carbon emission reductions by allocating climate funds from a fixed budget, $\bar{B}$, to specific Enova programs indexed by r, or to an alternative green policy. We let B_r denote the funding allocated to Enova's program area r and define $B_0 \equiv \bar{B} - \sum_r B_r$ as the amount of funding allocated to the alternative green policy.

Within each program area, the decision-maker receives a continuum of project applications p. Let $D = 1$ if the project application is accepted, in which the project receives a subsidy amount

$c(p)$, and let $D = 0$ if the project application is rejected. Let $Y_1(p)$ denote the potential project-level carbon emissions if the project is accepted, and let $Y_0(p)$ denote the potential carbon emissions if the project is rejected. Observed project-level carbon emissions, $Y(p)$, are related to potential carbon emissions through $Y(p) = Y_0(p) + D(Y_1(p) - Y_0(p))$. The causal effect on carbon emission of accepting the project can therefore be expressed as $\Delta(p) \equiv Y_1(p) - Y_0(p)$. Similarly, let Δ_0 denote the per Euro carbon emission effect that can be achieved in the alternative green policy.

As discussed in Section II.A, the decision-maker does not necessarily know the true carbon emission effect that would result from accepting the project, but forms an expectation $\mathcal{E}[\Delta \mid p]$ of the project's emission effect. Given these expectations, the decision-maker ranks each application. We let $q_r \in [0, 1]$ denote the percentile rank of project p within program area r. Given a budget allocation B_r to program r, climate funds are allocated within that program so that:

$$B_r = \int_{q_r^c}^{1} c(r, q_r)\, dq_r, \tag{2}$$

where q_r^c denotes the lowest-ranked (marginal) accepted project within the program area. A program's total carbon emission reduction, E_r, can then be expressed as:

$$E_r = \int_{q_r^c}^{1} \mathcal{E}[\Delta | r, q_r]\, dq_r,$$

The total carbon emission reduction from the budget allocations $\{B_r\}_{r=1}^{R}$ (Enova) and B_0 (alternative policy) is then given by:

$$\underbrace{\sum_r \int_{q_r^c}^{1} \mathcal{E}[\Delta | r, q_r]\, dq_r}_{\text{Emission reductions: Enova}} + \underbrace{\Delta_0 B_0}_{\text{Alternative policy}}.$$

B. *Decision problem and project selection rule*

Decision problem. The decision-maker's problem consists of choosing budget allocations $\{B_r\}_{r=1}^{R}$ and B_0 to maximize the objective function:

$$\max_{B_0,\{B_r\}_{r=1}^{R}} \underbrace{\sum_r \overbrace{\int_{q_r^c}^{1} \mathcal{E}[\Delta|r,q_r]\,dq_r}^{\text{Emission reductions}} + \overbrace{\beta_r B_r}^{\text{Other motives}}}_{\text{Enova}} + \underbrace{\Delta_0 B_0}_{\text{Alternative policy}}, \tag{3}$$

subject to the constraints:

$$i) \quad \bar{B} = B_0 + \sum_r B_r \qquad\qquad ii) \quad B_r = \int_{q_r^c}^{1} c(r,q_r)dq_r$$

The objective function captures that the decision-maker is instructed to allocate B_r to minimize carbon emissions. However, it also allows for the possibility that the decision-maker expresses other motives or preferences in the budget allocation. These motives may reflect the decision-maker's self-interest, or pressure to use funds to benefit other political goals and interest groups. For example, certain Enova programs may be systematically favored because they are visible to the public, popular among politicians, or expected to benefit certain groups or regions. These other motives are captured by β_r, which represents the utility derived from non-emission-related motives per Euro spent on program r.[15]

Given the decision problem in equation (3), the decision-maker's optimal funding allocation requires that the marginal benefit per subsidy Euro, $\frac{\mathcal{E}[\Delta|r,q_r]}{c(r,q_r)} + \beta_r$, is equalized across Enova's program areas and equal to the return Δ_0 on the alternative policy. The resulting first order condition lets us express the decision-maker's project selection rule as follows:

$$D = \mathbb{I}\Big\{ \frac{\mathcal{E}[\Delta|r,q_r]}{c(r,q_r)} \geq \Delta_0 - \beta_r \Big\}. \tag{4}$$

[15] With this notation, we align with the literature on detecting bias in decision-making (e.g., Becker, 1957 and Canay et al., 2023), where β_r is typically interpreted as a measure of "taste-based" discrimination.

Equation (4) makes precise three key determinants of how projects are selected. First, it captures the objective of maximizing carbon emission reductions per Euro while also allowing for motives that tilt the decisions toward certain program areas. Second, it specifies the information the decision-maker is using when selecting projects. We capture this through the conditioning set (r, q_r), which includes program and project-specific information from the individually ranked applications. Third, the model specifies how the decision-maker forms beliefs about the effects given the information available. The term $\mathcal{E}[\Delta|r, q_r]$ denotes the expected carbon emission effect given the beliefs of the decision-maker *ex-ante*, where the notation explicitly allows the subjective expectation to deviate from *ex-post* realized effects, which we denote $\Delta(r, q_r)$.

Throughout, we refer to emission reductions per Euro, $\frac{\Delta(r,q_r)}{c(r,q_r)}$, as *returns*. It is useful to define the difference between the decision-maker's expected return and the realized return as:

$$\lambda(r, q_r) \equiv \frac{\Delta(r, q_r)}{c(r, q_r)} - \frac{\mathcal{E}[\Delta|r, q_r]}{c(r, q_r)}. \tag{5}$$

This allows us to express the project selection rule in terms of ex-post realized returns:

$$D = \mathbb{I}\Big\{ \frac{\Delta(r, q_r)}{c(r, q_r)} \geq \Delta_0 - \beta_r + \lambda(r, q_r) \Big\}. \tag{6}$$

Equation (6) makes clear that the decision-maker accepts projects whenever the *realized* return exceeds the return in the alternative policy, adjusted for motives unrelated to carbon emissions, β_r, and deviations between expected and realized returns, $\lambda(r, q_r)$. The decision-maker may fund projects with inferior realized returns either because she has motives beyond emission reductions, is unable ex-ante to identify the projects with the highest ex-post returns, or both.

Using the selection rule in equation (4), we can express the total realized return achieved under

the decision-maker's allocation as:

$$\underbrace{\sum_{r} \int_{q_r^c}^{1} \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r}_{\text{Return on Enova projects}} + \underbrace{b_0 \ \Delta_0}_{\text{Return on alternative policy}} \tag{7}$$

where b_0 denotes the share of the total budget ($\bar{B}$) allocated to the alternative policy when the decision-maker selects projects according to the selection rule in equation (4).

C. Tests and measures of misallocation

To test for and measure misallocation, we first consider a counterfactual first-best allocation in which the decision-maker has no motives beyond carbon emission reductions and full knowledge of ex-post returns.

We define the first-best allocation by setting $\beta = \lambda = 0$. Let f_r denote the percentile rank of projects based on ex-post realized returns. The first-best selection rule is then:

$$\tilde{D} = \mathbb{I}\Big\{ \frac{\Delta(r, f_r)}{c(r, f_r)} \geq \Delta_0 \Big\}. \tag{8}$$

Here, the decision-maker simply funds the projects with the highest ex-post realized returns. We let f_r^c denote the marginally accepted projects in this allocation, whose return is Δ_0.

Test for misallocation. Assuming an interior solution (that is, the decision-maker would optimally allocate some funds to both the alternative policy and to each Enova program), equations (6) and (8) imply there is misallocation whenever the marginal returns on Enova's program areas differ from the marginal return in the first-best allocation:

$$\frac{\Delta(r, q_r^c)}{c(r, q_r^c)} \neq \frac{\Delta(r, f_r^c)}{c(r, f_r^c)} = \Delta_0 \tag{9}$$

To see why the inequality above implies misallocation, note that if marginal returns are not equal-

ized across programs and not equal the return of the alternative policy, the decision-maker can increase carbon emission reductions for the same level of spending by reallocating funds.

Measure of misallocation. We measure misallocation as the difference in total realized returns achieved under the selection rules in equations (6) and (8):

$$M \equiv \underbrace{\sum_r \int_{f_r^c}^1 \frac{\Delta(r, f_r)}{c(r, f_r)} df_r + b_0^f \Delta_0}_{\text{First best allocation}} - \underbrace{\sum_r \int_{q_r^c}^1 \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r + b_0 \Delta_0}_{\text{Actual allocation}} \tag{10}$$

where b_0^f denotes the share of the total budget ($\bar{B}$) that is allocated to the alternative policy when the decision-maker selects projects according to the first-best selection rule in equation (8). The first two terms in equation (10) represent the total carbon emission return achieved by a decision-maker with no motives other than carbon emission reductions and who knows ex-post realized returns; the last two terms represent the total return achieved by the actual decision-maker whose allocation may reflect other motives or prediction error about the ex-post realized returns.

D. Decomposition: Sources of misallocation

To understand the underlying sources of misallocation, we can decompose M from equation (10) into two parts: One that arises because the decision-maker may have other motives than carbon emission reductions, and one that arises because the decision-maker selects projects based on ex-ante expected returns, which may differ from the ex-post realized returns.

To perform this decomposition, it is useful to first define a second-best allocation in which the decision-maker has no motives other than emission reductions ($\beta = 0$) but selects projects based on ex-ante expected returns (λ could differ from zero). The second-best selection rule is:

$$D^{SB} = \mathbb{I}\Big\{ \frac{\mathcal{E}[\Delta | r, q_r]}{c(r, q_r)} \geq \Delta_0 \Big\}, \tag{11}$$

which implies that the ex-ante expected marginal returns are equalized across all program areas

within Enova and is equal to the return of the alternative policy:

$$\frac{\mathcal{E}[\Delta|r, q_r^s]}{c(r, q_r^s)} = \Delta_0, \qquad \forall\, r$$

where q_r^s denotes the marginally accepted projects in this allocation, whose expected return is Δ_0. The total realized return achieved under the selection rule in equation (11) is given by:

$$\underbrace{\sum_r \int_{q_r^s}^1 \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r}_{\text{Return on Enova projects}} + \underbrace{b_0^s\ \Delta_0}_{\text{Return on alternative policy}} \tag{12}$$

As we show in Appendix Section I.A, we can decompose misallocation into components that isolate the contribution from other motives and prediction errors by adding and subtracting the second-best allocation in equation (12) from our measure, M, of misallocation in equation (10):

$$\underbrace{M}_{\text{Misallocation}} = \underbrace{M_\beta}_{\text{Other motives}} + \overbrace{\underbrace{M_r}_{\text{Ranking error}} + \underbrace{\Lambda}_{\text{Realization error}}}^{\text{Misallocation from prediction errors}}, \tag{13}$$

where

$$\underbrace{M_\beta}_{\text{Other motives}} = \underbrace{\sum_r \int_{q_r^s}^1 \frac{\mathcal{E}[\Delta|r, q_r]}{c(r, q_r)}\, dq_r + b_0^s \Delta_0}_{\text{Second best: Expected return}} - \underbrace{\sum_r \int_{q_r^c}^1 \frac{\mathcal{E}[\Delta|r, q_r]}{c(r, q_r)} dq_r + b_0 \Delta_0}_{\text{Actual: Expected return}},$$

and

$$\underbrace{M_r}_{\text{Ranking error}} = \underbrace{\sum_r \int_{f_r^c}^1 \frac{\Delta(r, f_r)}{c(r, f_r)} df_r + b_0^f \Delta_0}_{\text{First best: Realized return}} - \underbrace{\sum_r \int_{q_r^s}^1 \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r + b_0^s \Delta_0}_{\text{Second best: Realized return}},$$

and

$$\underbrace{\Lambda}_{\text{Realization error}} = \sum_r \Bigg(\underbrace{\int_{q_r^s}^1 \lambda(r, q_r)\, dq_r}_{\text{Second best: Realization error}} - \underbrace{\int_{q_r^c}^1 \lambda(r, q_r)\, dq_r}_{\text{Actual: Realization error}} \Bigg).$$

The component M_β captures that the decision-maker may allocate too much funding to Enova as

opposed to the alternative policy, or favor certain Enova program areas over others. The components M_r and Λ capture misallocation due to prediction errors. These errors can distort project rankings, as captured by M_r, and create discrepancies between ex-ante and ex-post returns for a given selection of projects, as captured by Λ. While Λ contributes to misallocation relative to the first-best allocation, it does not cause misallocation relative to the second-best allocation.

E. Decomposition: Margins of misallocation

The decision-maker has two choice margins in our model: She must choose how much to allocate to Enova and, given this allocation, how to allocate funds across Enova programs. Consequently, misallocation can arise both from *overspending* on Enova and *misspending* within Enova. We now decompose M from equation (10) to quantify the relative importance of these margins of misallocation.

To perform this decomposition, it is useful to define a first-best "autarky" allocation, where the decision-maker cannot allocate funds to the alternative policy. Let f_r^A denote the marginally accepted Enova projects in this first-best autarky allocation, where realized returns are equalized across programs. The total return under the first-best autarky allocation is then:

$$\sum_r \int_{f_r^A}^1 \frac{\Delta(r, f_r)}{c(r, f_r)} df_r \tag{14}$$

With this definition, we can rewrite our measure of misallocation from equation (10) as:

$$M = \underbrace{\sum_r \left(\int_{f_r^c}^1 \frac{\Delta(r, f_r)}{c(r, f_r)} df_r + \int_{f_r^A}^{f_r^c} \Delta_0 \, df_r \right)}_{\text{First best allocation}} - \underbrace{\sum_r \int_{q_r^c}^1 \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r + b_0 \Delta_0}_{\text{Actual allocation}} \tag{15}$$

The first term in the first-best allocation represents the return on funds allocated to Enova, where the decision-maker selects all projects within the budget with a higher return than what is achievable in the alternative policy. The second term represents the return on the remaining funds, which are

allocated to the alternative policy, funding all projects ranked between f_r^A and f_r^c.

Adding and subtracting the first-best autarky allocation in equation (14) from our measure of total misallocation in equation (15), we can decompose M as follows:

$$M = \underbrace{\left(\sum_r \int_{f_r^A}^{f_r^c} \Delta_0 - \frac{\Delta(r, f_r)}{c(r, f_r)} df_r \right) - b_0 \Delta_0}_{\text{Overspending on Enova: } M^O} + \underbrace{\left(\sum_r \int_{f_r^A}^{1} \frac{\Delta(r, f_r)}{c(r, f_r)} df_r - \int_{q_r^c}^{1} \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r \right)}_{\text{Misspending within Enova: } M^S} \quad (16)$$

The component M^O captures overspending on Enova, measured as the loss in realized return from funding Enova projects that yield a return below that of the alternative policy. The component M^S captures misspending within Enova, measured as the loss in realized return due to differences in marginal returns across Enova's programs, for a fixed level of spending.

As we show in Appendix Section I.B, these two components can be further decomposed into sources related to the decision-maker's non-emission motives and prediction errors. We achieve this by defining a second-best autarky allocation, analogous to the first-best autarky allocation above, but where the decision-maker selects projects based on ex-ante rather than ex-post returns. Adding and subtracting the return on the second-best autarky allocation, and using our definition of λ from equation (5), we can then decompose M from equation (10) as follows:

$$M = \underbrace{M_r^O + M_\beta^O + \Lambda^O}_{\text{Overspending on Enova}} + \underbrace{M_r^S + M_\beta^S + \Lambda^S}_{\text{Misspending within Enova}}, \quad (17)$$

where

$$M_\beta^O = \underbrace{\left(\sum_r \int_{q_r^s}^{1} \Delta_0 - \frac{\mathcal{E}[\Delta | r, q_r]}{c(r, q_r)} dq_r \right) - b_0 \Delta_0}_{\text{Overspending due to other motives}},$$

and

$$M_r^O = \underbrace{\sum_r \int_{f_r^A}^{f_r^c} \Delta_0 - \frac{\Delta(r, f_r)}{c(r, f_r)} df_r - \sum_r \int_{q_r^A}^{q_r^s} \Delta_0 - \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r}_{\text{Overspending due to ranking errors}},$$

and

$$\Lambda^O = \underbrace{-\sum_r \int_{q_r^A}^{q_r^s} \lambda(r, q_r) dq_r}_{\text{Realization errors for overspending}},$$

and

$$M_\beta^S = \underbrace{\sum_r \int_{q_r^A}^1 \frac{\mathcal{E}[\Delta|r, q_r]}{c(r, q_r)} dq_r - \sum_r \int_{q_r^c}^1 \frac{\mathcal{E}[\Delta|r, q_r]}{c(r, q_r)} dq_r}_{\text{Misspending due to other motives}},$$

and

$$M_r^S = \underbrace{\sum_r \int_{f_r^A}^1 \frac{\Delta(r, f_r)}{c(r, f_r)} df_r - \sum_r \int_{q_r^A}^1 \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r}_{\text{Misspending due to ranking errors}},$$

and

$$\Lambda^S = \underbrace{\sum_r \int_{q_r^A}^1 \lambda(r, q_r) dq_r - \sum_r \int_{q_r^c}^1 \lambda(r, q_r) dq_r}_{\text{Realization error for misspending}}.$$

IV. Implementing the Tests and Measures of Misallocation

We now explain how we implement the tests and measures of misallocation introduced in Section III, before presenting our empirical findings in Section V.

A. Testing for misallocation

To test for misallocation, it follows from equation (9) that we need data on realized carbon emission returns, $\frac{\Delta(r,q_r^c)}{c(r,q_r^c)}$, for marginally accepted Enova projects as well as the counterfactual return, Δ_0, that could have been achieved in an alternative policy.

As explained in Section II.B, we directly observe the decision-maker's expectation about the carbon emission effect, $\mathcal{E}[\Delta|r, q_r]$, as well as the ex-post realized carbon emission effect, $\Delta(r, q_r)$, for

all accepted Enova projects. In addition, we observe the subsidy amount, c, for all Enova projects. This allows us to compute $\frac{\mathcal{E}[\Delta|r,q_r]}{c(r,q_r)}$ and $\frac{\Delta(r,q_r)}{c(r,q_r)}$ for all accepted projects. Consistent with the model and the institutional arrangement, we rank all accepted projects based on $\frac{\mathcal{E}[\Delta|r,q_r]}{c(r,q_r)}$ to identify q_r^c as the marginally accepted Enova projects in the decision-maker's actual allocation. We repeat this ranking by program area and year.

In our main analysis, we use the purchase and deletion of carbon emission quotas from the EU Emissions Trading System as the decision-maker's alternative policy. Since these emission quotas are traded on a spot market, they have a known price and return. We measure the carbon emission return in the alternative policy as $\Delta_0 = \frac{1}{\phi}$, where ϕ denotes the EUR price per ton of CO_2 emissions in the EU ETS.[16] In robustness analyses in Section V.F, we present results based on other alternative policies.

B. Measuring misallocation: The anatomy of the identification problem

While it is straightforward to test for the presence of any misallocation, it is more challenging to quantify the total amount of misallocation. The key data challenge in measuring misallocation is that we do not observe the expected and realized carbon emission returns for rejected Enova projects. To clarify the identification challenge, it is useful to rewrite M from equation (10) in terms of the decision-maker's loss in returns due to Type I errors (wrongly rejected projects) and Type II errors (wrongly accepted projects):

[16] As explained in Section III.A, we assume that the carbon emission effect in the alternative policy, Δ_0, is unaffected by the decision-maker's total level of spending on the alternative policy, B_0. This is a reasonable assumption in our setting since the EU ETS market for emission quotas is large relative to Norway's spending.

Lemma 1: *Total misallocation, M, can be expressed as the sum of lost realized returns due to Type I (wrongly rejected projects) and Type II errors (wrongly accepted projects):*

$$M = \sum_r \frac{1}{\bar{B}} \int_0^1 \underbrace{\mathbb{I}[\tilde{D} > D]\left(\frac{\Delta(r,f_r)}{c(r,f_r)} - \Delta_0\right) c(r,f_r)}_{\text{Type I: Wrongly rejected projects}} + \underbrace{\mathbb{I}[\tilde{D} < D]\left(\Delta_0 - \frac{\Delta(r,f_r)}{c(r,f_r)}\right) c(r,f_r)}_{\text{Type II: Wrongly accepted projects}} \, df_r \quad (18)$$

Proof. See Appendix Section I.C.

The first term of Lemma 1 reflects the loss in realized returns from rejecting Enova projects with returns that exceed the return of the alternative policy (Type I error), and the second term of Lemma 1 reflects the loss in realized returns from accepting Enova projects with returns below the return of the alternative policy (Type II error). However, since we do not observe the realized returns on rejected Enova projects, we cannot measure the Type I errors. In the following, we take two approaches to resolving this identification challenge.

C. Constructing lower and upper bounds on misallocation

The first approach involves constructing bounds on M. Using our data on the realized returns on accepted Enova projects, we can construct worst-case bounds on M. While the worst-case *upper* bound is infinite, the worst-case lower bound is informative as the Type I errors are weakly positive. The following proposition gives an analytical expression of the worst-case bounds:

Proposition 1a: Worst case bounds: *It follows from Lemma 1 that the worst-case upper and lower bounds of misallocation, M, are given by:*

$$M \in [M^{LB}, \infty),$$

$$\text{where} \quad M^{LB} = M^{\text{TypeII}} \equiv \sum_r \frac{1}{\bar{B}} \int_0^1 \underbrace{I[\tilde{D} < D]\left(\Delta_0 - \frac{\Delta(r,f_r)}{c(r,f_r)}\right) c(r,f_r)}_{\text{Type II: Wrongly accepted projects}} \, df_r$$

By making assumptions about the Type I errors in Lemma 1, we can also construct an informative upper bound on M. To construct such an upper bound, it is useful to rewrite the Type I term of Lemma 1 as:

Lemma 2: *Misallocation due to Type I (wrongly rejected projects) can be written as:*

$$\sum_r \frac{1}{\bar{B}} \Bigg(\underbrace{\frac{\mathbb{E}[\Delta \mid r, \tilde{D}=1, D=0]}{\mathbb{E}[c \mid r, \tilde{D}=1, D=0]} - \Delta_0}_{\text{Return on wrongly rejected projects}} \Bigg) * \underbrace{\mathbb{E}[c \mid r, \tilde{D}=1, D=0]}_{\text{Cost of wrongly rejected projects}} * \underbrace{\mathbb{P}[\tilde{D}=1 \cap D=0 \mid r]}_{\text{Prevalence of wrongly rejected projects}}$$

where the first term captures the difference in average returns between the wrongly rejected projects and the alternative policy, the second term consists of the average subsidy cost of wrongly rejected projects, and the last term is the share of projects that are wrongly rejected. While each of these three terms are unobserved in the data, they can be bounded.

The share of wrongly rejected projects cannot exceed the *total* share of rejected projects, which means that $\mathbb{P}[\tilde{D}=1 \cap D=0 \mid r] \leq \mathbb{P}(D=0 \mid r)$. The misallocation due to Type I errors is maximized if all rejected projects are wrongly rejected. We would then have that $\mathbb{P}[\tilde{D}=1 \cap D=0 \mid r] = \mathbb{P}(D=0 \mid r)$ and $\mathbb{E}[c \mid r, \tilde{D}=1, D=0] = \mathbb{E}[c \mid r, D=0]$, which is observed in the data.[17]

By assuming that the average realized return on correctly accepted projects is weakly larger than that of wrongly rejected projects, we can also bound the return on wrongly rejected projects:

Assumption 1: Ex-post monotone treatment selection. *The average return of correctly accepted Enova projects exceeds the average return of wrongly rejected projects within the same program area.*

$$\underbrace{\frac{\mathbb{E}[\Delta \mid r, \tilde{D}=1, D=1]}{\mathbb{E}[c \mid r, \tilde{D}=1, D=1]}}_{\text{Return on correctly accepted projects: Observed}} \geq \underbrace{\frac{\mathbb{E}[\Delta \mid r, \tilde{D}=1, D=0]}{\mathbb{E}[c \mid r, \tilde{D}=1, D=0]}}_{\text{Return on wrongly rejected projects: Unobserved}}$$

[17] While we do not observe the realized carbon emission returns, $\frac{\Delta}{c}$, of rejected Enova projects, we do observe the requested subsidy amount, c, for both accepted ($D=1$) and rejected ($D=0$) Enova projects.

This assumption is weaker than the common selection gains assumption in the treatment effects literature (see, for example, Manski, 1997). It simply states that the returns of projects that are correctly accepted are, on average, higher than those of projects that are wrongly rejected. This would hold, for example, if the decision-maker observes a noisy measure of true returns.

Under Assumption 1, we can construct the following bounds on M:

Proposition 1b: Monotone treatment selection bounds. *Under Assumption 1, it follows from Lemma 2 that the lower and upper bounds on misallocation M are given by:*

$$M \in [M^{LB}, M^{UB}],$$

$$\text{where} \quad M^{UB} = \sum_r \frac{1}{\bar{B}} \underbrace{\left(\frac{\mathbb{E}[\Delta \mid r, \tilde{D} = 1, D = 1]}{\mathbb{E}[c \mid r, \tilde{D} = 1, D = 1]} - \Delta_0 \right) \mathbb{E}[c \mid r, D = 0] * P[D = 0 \mid r]}_{\text{Wrongly rejected projects: Upper bound}} + M^{\text{TypeII}}$$

Proof: See Appendix Section I.D.

D. Constructing lower and upper bounds on the sources of misallocation

It is also possible to construct bounds on the *sources* of misallocation. To do so, we first construct bounds on M_β (misallocation due to other motives), the source of primary interest, and then use information about these bounds to construct consistent bounds on M_r and λ (misallocation due to prediction errors).

To clarify the identification challenge, it is useful to rewrite M_β from equation (13) in terms of the decision-maker's loss in expected returns due to ex-ante Type I errors (ex-ante wrongly rejected projects) and ex-ante Type II errors (ex-ante wrongly accepted projects):

Lemma 3: *M_β can be expressed as the total loss in expected returns due to ex-ante Type I errors (wrongly rejected projects) and ex-ante Type II errors (wrongly accepted projects).*

$$M_\beta = \sum_r \frac{1}{\bar{B}} \int_0^1 \underbrace{\mathbb{I}[D^{SB} > D]\left(\frac{\mathcal{E}[\Delta|r,q_r]}{c(r,q_r)} - \Delta_0\right) c(r,q_r)}_{\text{Type I: Ex-ante wrongly rejected projects}} + \underbrace{\mathbb{I}[D^{SB} < D]\left(\Delta_0 - \frac{\mathcal{E}[\Delta|r,q_r]}{c(r,q_r)}\right) c(r,q_r)}_{\text{Type II: Ex-ante wrongly accepted projects}} \quad dq_r$$

Proof: See Appendix Section I.E.

Since we observe the expected returns for accepted but not rejected projects, we can directly measure the Type II errors of Lemma 3, but not the Type I errors. However, using our data on the expected returns of accepted projects, it follows from Lemma 3 that we can construct worst-case bounds on M_β:

Proposition 2a: Worst case bounds: *The worst-case upper and lower bounds on misallocation from other motives, M_β, are given by :*

$$M_\beta \in [M_\beta^{LB}, \infty),$$

$$\text{where} \quad M_\beta^{LB} = M_\beta^{\text{TypeII}} \equiv \sum_r \frac{1}{\bar{B}} \int_0^1 \underbrace{\mathbb{I}[D^{SB} < D]\left(\Delta_0 - \frac{\mathcal{E}[\Delta|r,q_r]}{c(r,q_r)}\right) c(r,q_r)}_{\text{Type II: Ex-ante wrongly accepted projects}} \quad dq_r$$

To construct an informative upper bound on M_β, we again assume that the average return on correctly accepted projects is weakly larger than for wrongly rejected projects, but this time the assumption is made for the ex-ante *expected* carbon emission returns:

Assumption 2: Ex-ante monotone treatment selection. *The average ex-ante expected return of correctly accepted Enova projects exceeds that of wrongly rejected projects within the same program area.*

$$\frac{\mathbb{E}\left[\mathcal{E}[\Delta] \mid r, D^{SB} = 1, D = 1\right]}{\mathbb{E}\left[c \mid r, D^{SB} = 1, D = 1\right]} \geq \frac{\mathbb{E}\left[\mathcal{E}[\Delta] \mid r, D^{SB} = 1, D = 0\right]}{\mathbb{E}\left[c \mid r, D^{SB} = 1, D = 0\right]}$$

Under Assumption 2, we can construct the following bounds on M_β:

Proposition 2b: Ex-ante monotone treatment selection bounds. *Under Assumption 2, it follows from Lemma 3 that the lower and upper bound of misallocation from other motives, M_β, is given by:*

$$M_\beta \in [M_\beta^{LB}, M_\beta^{UB}],$$

$$\text{where} \quad M_\beta^{UB} = \sum_r \frac{1}{\overline{B}} \underbrace{\left(\frac{\mathbb{E}\left[\mathcal{E}[\Delta] \mid r, D^{SB}=1, D=1\right]}{\mathbb{E}\left[c \mid r, D^{SB}=1, D=1\right]} - \Delta_0 \right) \mathbb{E}[c \mid r, D=0]\, \mathbb{P}[D=0 \mid r]}_{\text{Upper bound on Type I: Ex-ante wrongly rejected projects}} + M_\beta^{\text{TypeII}}$$

Proof: See Appendix Section I.F.

It follows directly from Proposition 2b and the decomposition in equation (13) that it is possible to construct bounds on the total prediction error, $M_r + \Lambda$. Since misallocation from ranking errors, M_r, is defined as the difference in realized return between the first-best and the second-best allocation, it follows that $M_r > 0$. This allows us to construct the following bounds on total prediction errors ($M_r + \Lambda$), ranking errors (M_r), and the realization gap (Λ), which we state in Proposition 3.

Proposition 3: Consistent bounds on $M_r + \Lambda$, M_r, and Λ:

a. *The total prediction error $M_r + \Lambda$ is bounded by:*

$$M_r + \Lambda \in [M^{LB} - M_\beta^{UB}, M^{UB} - M_\beta^{LB}].$$

b. *The ranking error M_r is bounded by:*

$$M_r \in [0, \infty).$$

c. *The realization gap* Λ *is bounded by*:

$$\Lambda \in (-\infty\ ,\ M^{UB} - M_{\beta}^{LB}].$$

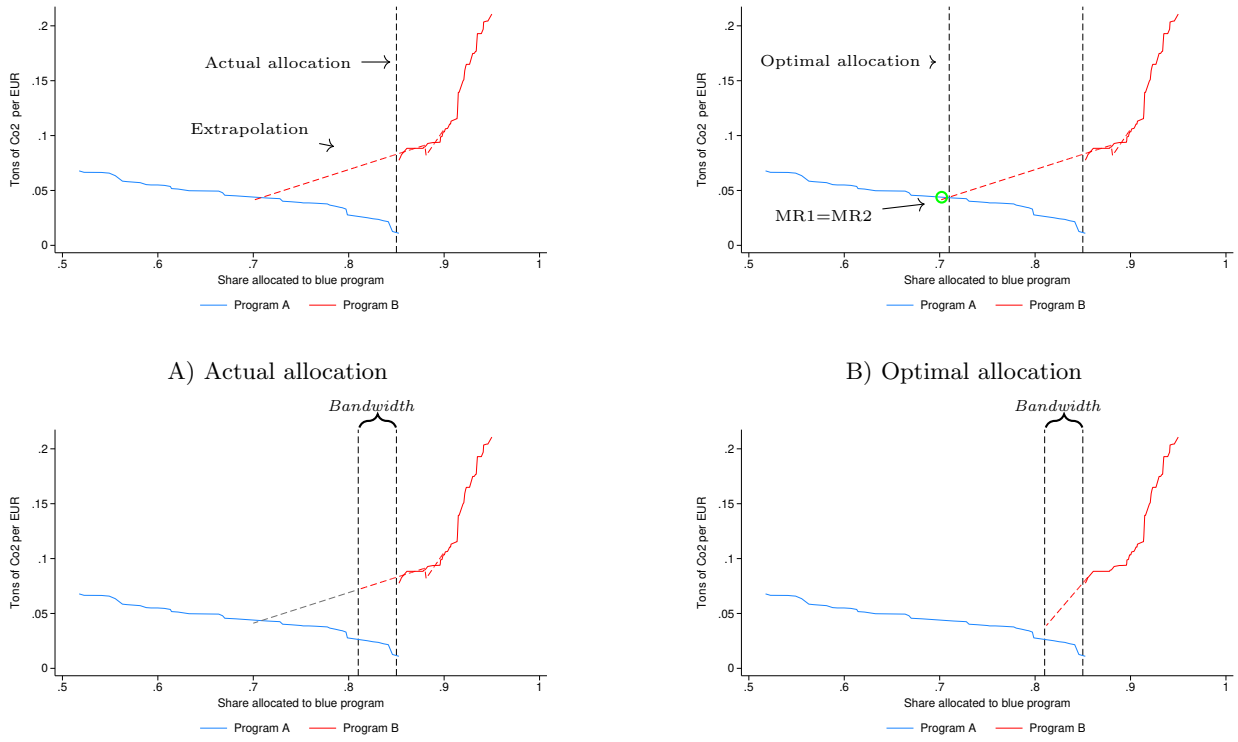
E. Extrapolation to achieve point identification of misallocation

The second approach involves point identification of total misallocation M, the sources of misallocation (M_{β}, M_r, Λ), and the margins of misallocation (M^O, M^S). The point identification argument is useful for two reasons. First, if the assumptions hold, it allows us to draw stronger conclusions than the bounds. Second, it is challenging to construct bounds on the margins of misallocation, which means point identification is particularly useful for quantifying these margins.

To achieve point identification, we follow Cingano et al. (2025) in extrapolating expected and realized emission returns from marginally accepted to rejected Enova projects. Given estimates of the expected and realized returns of both accepted and rejected Enova projects, it follows from equations (10), (13), and (16) that we can point-identify M, its sources, and margins.

Figure 4 illustrates the extrapolation approach for two major program areas, Program A ("*Energy and Climate Initiatives in Industry*") and Program B ("*Heating Plants*"). Panel A shows that marginal realized returns are not equalized across these programs, allowing us to directly reject the hypothesis of no misallocation. In particular, the decision-maker could achieve higher returns for the same level of spending by reallocating funds from Program A to Program B. This reallocation would shift the horizontal line in Figure 4 to the left, allowing previously rejected projects in Program B to be accepted instead. How far an unbiased decision-maker ($\lambda = 0$ and $\beta = 0$) would shift the line depends on the returns of rejected projects in Program B. While we do not directly observe these returns, we can estimate them by extrapolating from the accepted projects in Program B, as shown by the dotted line in Panel B. In the baseline analysis, we extend this extrapolation until marginal returns are equalized between programs, as illustrated in Panel B.

Extrapolating expected and realized emission returns far from the marginally accepted projects



A) Actual allocation

B) Optimal allocation

C) Changing the bandwidth

D) Changing the slope

Figure 4. Illustration: Extrapolating returns. This figure illustrates how we extrapolate carbon emission returns from accepted to rejected Enova projects in the context of two program areas, Program A ("*Energy and Climate Measures in Industry*") and Program B ("*Heating Plants*"). Panel A shows expected emission returns for projects in Program A, sorted from highest (left) to lowest (right), and for projects in Program B, sorted from highest (right) to lowest (left). The dotted line represents a linear extrapolation from the lowest-return accepted project in Program B. Panel B illustrates the same setup but highlights the optimal allocation where marginal returns are equalized. Panel C applies a narrower bandwidth for reallocation, restricting the extent to which funds can be shifted between programs. Panel D illustrates a linear extrapolation where the slope is artificially steepened by 50%.

can potentially create bias in our misallocation point estimates. We take several steps to examine and mitigate this concern. First, we apply our extrapolation procedure to stated returns reported by firms in their subsidy applications, which are observed for *all* projects, including rejected ones. This allows us to compare the accuracy of the prediction procedure to a known ground truth. The results are presented in Figure 5. Reassuringly, the extrapolated stated returns closely follow the observed stated returns for rejected projects, suggesting that the extrapolation method performs well when applied to a set of universally-observed carbon emission returns.

Another step we take to address concerns about the extrapolation approach is to report estimates using a wide range of estimation bandwidths, as illustrated in Panel C of Figure 4. Since reducing the estimation bandwidth limits the extent of reallocation the decision-maker can implement relative to the (unrestricted) decision-maker considered in Section III, it mechanically lowers the estimated misallocation. As a final sensitivity check, we will also report estimates where we conservatively assess misallocation by imposing a steeper slope on the extrapolation from marginally accepted to rejected projects, as illustrated in Panel D of Figure 4.

V. Tests and Measures of Misallocation

We now present our empirical results on misallocation. In Sections V.A and V.B, we test for and measure misallocation. Next, in Sections V.C and V.D, we decompose misallocation into its sources and margins. Lastly, in Sections V.F–V.G, we conduct a wide range of robustness tests.

Throughout this section, we estimate returns separately by program area and year. We use these returns to rank projects within each program area and year and to identify the first- and second-best allocations. Next, we calculate the annual carbon emission returns achieved under the first- and second-best allocations, as well as under the actual allocation of accepted Enova projects. Finally, we combine these estimates to obtain annual cost-weighted average differences in returns, which serves as our primary metric of misallocation. As an alternative metric, we also scale this return estimate by the total amount of Enova spending to express misallocation in terms of tons

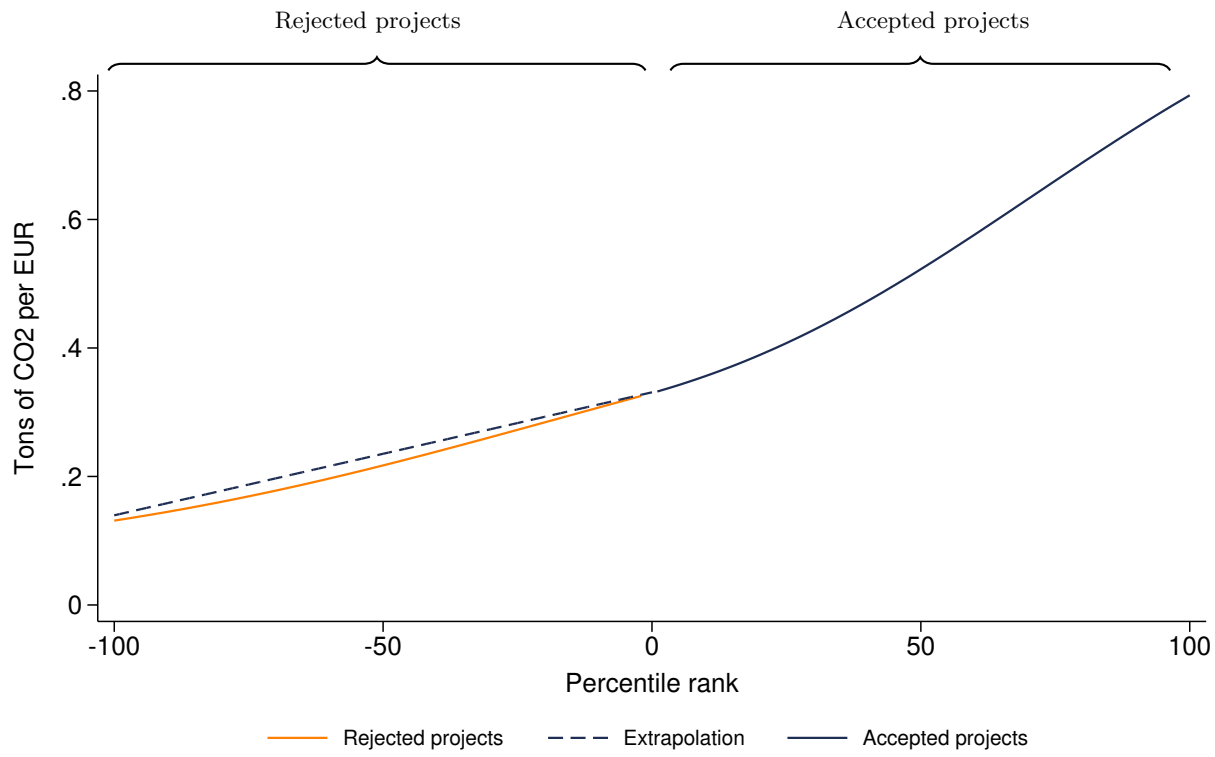


Figure 5. Illustration: Extrapolating stated returns. The figure applies our extrapolation procedure to stated emission returns reported by firms in their subsidy applications, which are observed for all projects, including rejected ones. The blue line shows the stated return of accepted projects, plotted against the percentile rank of stated returns among accepted projects. Accordingly, the leftmost point on the blue line corresponds to the accepted project with the lowest stated return. The orange line shows the stated return of rejected projects, plotted against the percentile rank of stated returns among rejected projects. Accordingly, the rightmost point on the orange line corresponds to the rejected project with the highest stated return. Since the rejected project with the highest stated return can have a stated return above the accepted project with the lowest stated return, we shift the blue and orange lines so that their intercepts coincide at percentile rank 0. This normalization mimics the case of evaluated returns, where rejected projects have strictly lower evaluated returns than accepted ones. The solid orange and blue lines are smoothed using a kernel-weighted local linear regression with a bandwidth of 40 percentile rank points. The dashed line shows the extrapolation from a linear regression of stated returns on the percentile rank for accepted projects.

of forgone carbon emission reductions.

A. Testing for misallocation

Recall from equation (9) that we have misallocation whenever marginal realized returns are not equalized across Enova's program areas and not equal to the return of the alternative policy. We present our tests of misallocation in Figure 6.

There are two key insights from Figure 6. The first is that there is considerable dispersion in marginal realized returns across Enova's program areas, with a standard deviation in marginal returns of 0.033 tons of CO_2 per Euro. The differences in marginal returns are significant: We can strongly reject the null hypothesis of equalized returns (with p-value smaller than 0.001).

The second is that a large majority of Enova programs have marginal returns that are below the return of the alternative policy. We can strongly reject the null that these marginal returns are equal to the return of the alternative policy at any conventional level of statistical significance (with p-value smaller than 0.001), suggesting pervasive misallocation at least on the margin.

B. Measuring total misallocation

As explained in Section IV, the loss in realized returns from accepting Enova projects with returns below the return of the alternative policy forms a so-called worst-case or no-assumption lower bound on total misallocation. The lower bound can be computed directly from Figure 7, which plots the realized return of accepted Enova projects together with the return on the alternative policy. We find that approximately 60% of accepted Enova projects have realized returns below what could be achieved in the EU ETS, resulting in a loss indicated by the gray-shaded area in Figure 7. We present the corresponding lower bound estimate of misallocation in column (1) of Panel A, Table III. We find that by optimally reallocating funds, the decision-maker could have increased carbon emission returns by at least 0.051 tons of CO_2 per Euro, which corresponds to 91% of the (cost-

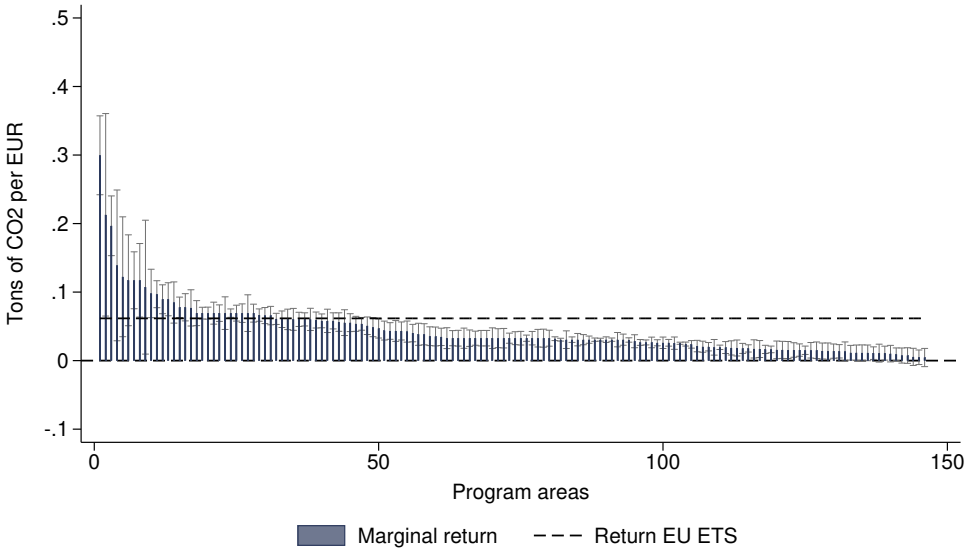


Figure 6. Testing for misallocation. The blue bars show the marginal realized carbon emission return on Enova projects, calculated separately by program area and year. The marginal realized return is defined as the lowest percentile return among accepted projects within a given program area and year. The gray spikes indicate 95% confidence intervals based on bootstrapped standard errors. The horizontal dotted line indicates the cost-weighted average return on carbon emission quotas in the EU ETS over the sample period.

weighted) average return on accepted Enova projects.[18] Scaling this estimate by total spending, we find that this lower bound estimate amounts to 2.3 million tons of forgone emission reductions, or about 4% of Norway's total annual emissions. Put differently, Enova could have achieved the current level of carbon emission reductions with 52% or less expenditure.[19]

We present our upper bound estimate of misallocation in column (3) of Panel A, Table III, which is based on Proposition 1b. We obtain an upper bound of 0.090 tons of CO_2 per Euro, which means the decision-maker could achieve at most 0.090 higher returns — corresponding to 161% of the average return on accepted projects — for the same level of spending by optimally reallocating funds.

[18] The cost-weighted average return of accepted Enova projects is 0.056 tons of CO_2 per Euro.

[19] We arrive at this number by dividing the return on the actual allocation by the lower bound return for the first-best allocation. The lower bound return on the first-best allocation is given by the return on the actual allocation (0.056 tons of CO_2 per Euro) plus the lower bound estimate of misallocation (0.051 tons of CO_2 per Euro).

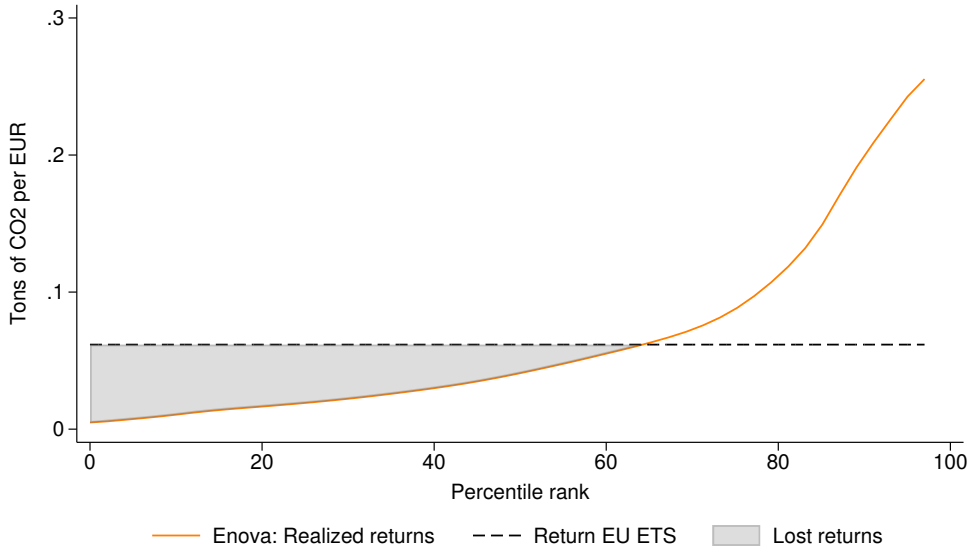


Figure 7. Bounding misallocation. The figure shows the percentile distribution of realized carbon emission returns for accepted Enova projects. The horizontal dotted line indicates the cost-weighted average return on carbon emission quotas in the EU ETS over the sample period. The gray shaded area represents the loss in returns from funding Enova projects with returns below those attainable in the EU ETS.

To obtain a point estimate of total misallocation, we extrapolate returns from marginally accepted to rejected Enova projects. Then, we measure misallocation as the difference between the realized return in the decision-maker's actual allocation and the counterfactual first-best allocation, following equation (10). Our point estimate is presented in column (2) of Panel A, Table III. We find that Enova could have increased its emission return by 0.052 tons of CO_2 per Euro by optimally reallocating funds, corresponding to 93% of the average return on accepted projects. Thus, the point estimate is very close to the lower bound estimate in column (1).

C. Sources of misallocation

It follows from equation (13) that we can decompose our point estimate of misallocation into parts driven by the decision-maker's non-emission motives (M_β) and prediction errors ($M_r + \Lambda$). We present this decomposition in column (2) of Panel B, Table III. We find that misallocation

Table III. Misallocation and Its Sources

	Return			Emission		
	Lower bound (1)	*Point estimate* (2)	*Upper bound* (3)	*Lower bound* (4)	*Point estimate* (5)	*Upper bound* (6)
Panel A: Total misallocation						
M	0.051	0.052	0.090	2.349	2.395	4.145
Panel B: Misallocation due to other motives						
M_β	0.046	0.050	0.101	2.119	2.303	4.652
Panel C: Misallocation due to prediction errors						
$M_r + \Lambda$	-0.050	0.002	0.044	-2.303	0.092	2.027
M_r	0.000	0.001	∞	0.000	0.046	∞
Λ	$-\infty$	0.001	0.044	$-\infty$	0.046	2.027

Notes: Panel A shows our bounds and point estimate of total misallocation, M, as given by Proposition 1b and equation (10), respectively. Panels B and C show our bounds and point estimates of the sources of misallocation, as given by Proposition 2b, Proposition 3, and equation (13). We report misallocation in terms of tons of CO_2 per Euro (*Return*) and million tons of CO_2 (*Emissions*).

is almost entirely driven by non-emission motives. Specifically, 96% of total misallocation can be attributed to the decision-maker's non-emission motives, compared to only 4% for prediction errors. Thus, the results suggest that the decision-maker is able to predict realized returns but is unwilling to systematically select the highest-returning projects.

A possible concern with this conclusion is that it rests on the assumptions needed to achieve point identification. It is therefore useful to also compute the bounds on the importance of the decision-maker's non-emission motives. We present these bounds in columns (1) and (3) of Panel B, Table III. We obtain lower and upper bound estimates of M_β of 0.046 and 0.101. By dividing the lower bound on M_β by the upper bound on M, we conclude that at least 44% of total misallocation is accounted for by the decision-maker's non-emission motives. For completeness, we also compute bounds on total prediction errors ($M_r + \Lambda$) and its components, following Proposition 3. As shown in Panel C of Table III, these bounds are less informative because Λ can be either positive or

Table IV. Margins of Misallocation

	Return	Emission
Panel A: Margins of misallocation		
M^O	0.047	2.165
M^S	0.005	0.230
Panel B: Decomposing the margins		
M^O_β	0.040	1.842
M^O_r	0.000	0.000
Λ^O	0.007	0.322
M^S_β	0.010	0.461
M^S_r	0.001	0.046
Λ^S	-0.006	-0.276

Notes: The table shows point estimates of the margins of misallocation and its decomposition, as given by equations (16) and (17). We report misallocation in terms of tons of CO_2 per Euro (*Return*) and million tons of CO_2 (*Emissions*).

negative.

D. Margins of misallocation

It follows from equation (16) that we can decompose our point estimate of misallocation into parts capturing overspending on Enova (M^O) and misspending within Enova (M^S). We present this decomposition in Panel A of Table IV. We find that the most important margin for reducing misallocation is to reduce spending on Enova relative to the alternative policy. By optimally reallocating funds away from Enova, the decision-maker could increase returns by 0.047 tons of CO_2 per Euro, corresponding to about 84% of the average return on accepted projects. That said, misallocation within Enova is also non-negligible. By optimally reallocating funds across Enova's programs, the decision-maker could further increase returns by 0.005 tons of CO_2 per Euro, corresponding to about 9% of the average return and 10% of total misallocation.

In Panel B of Table IV, we further decompose our point estimate of overspending and mis-

spending into parts related to the decision-maker's non-emission motives and prediction errors, as described in equation (17). We find that non-emission motives are the primary driver of overspending, accounting for more than 80% of overspending on Enova. Non-emission motives also dominate the misspending component. These results indicate that errors in predicting returns play a minor role in misallocation compared to non-emission motives, both in the allocation of funds across Enova's programs and in the allocation of funds between Enova and the alternative policy.

E. Correlates of misallocation

As explained in Section II, program areas are grouped by Enova into seven broad topic areas, reflecting the different types of green technologies eligible for subsidy. A natural question is whether funding is systematically skewed towards certain technologies. To answer this question, Figure 8 plots the correlation between each topic area and the expected marginal return relative to the alternative policy, $\frac{\mathcal{E}[\Delta|r,q_r]}{c(r,q_r)} - \Delta_0$. We focus on expected marginal returns to isolate variation in misallocation due to other motives. A negative correlation means that programs in that topic area are relatively overfunded, as reflected by low returns on the margin.

The correlations suggest that certain topics, such as land transportation, systematically receive too much funding, while others, such as energy systems and heating, receive too little. The gap is statistically and economically significant: On average, marginal returns are three times higher for the most underfunded topic area as compared to the most overfunded topic area. The differences in mean returns across topic areas also explain a substantial share of the variation in marginal returns across programs. Performing an ANOVA decomposition, we find that 23% of the overall variation is due to differences in mean returns between topic areas, while the remaining 77% is explained by differences in returns within topic areas.

A possible explanation for why certain topic areas systematically receive too much funding is that some green technologies are particularly popular among politicians. To assess this possibility, we examine whether overfunded topic areas receive additional funds through appropriation bills,

thereby bypassing Enova's normal block grants. Such earmarking typically arises during multi-party budget negotiations in Parliament to form majority coalitions. Reviewing the budget resolutions over our sample period, we find that Norwegian politicians have earmarked funds to programs in two topic areas — land transportation and maritime transportation — both of which are relatively overfunded with low marginal returns.

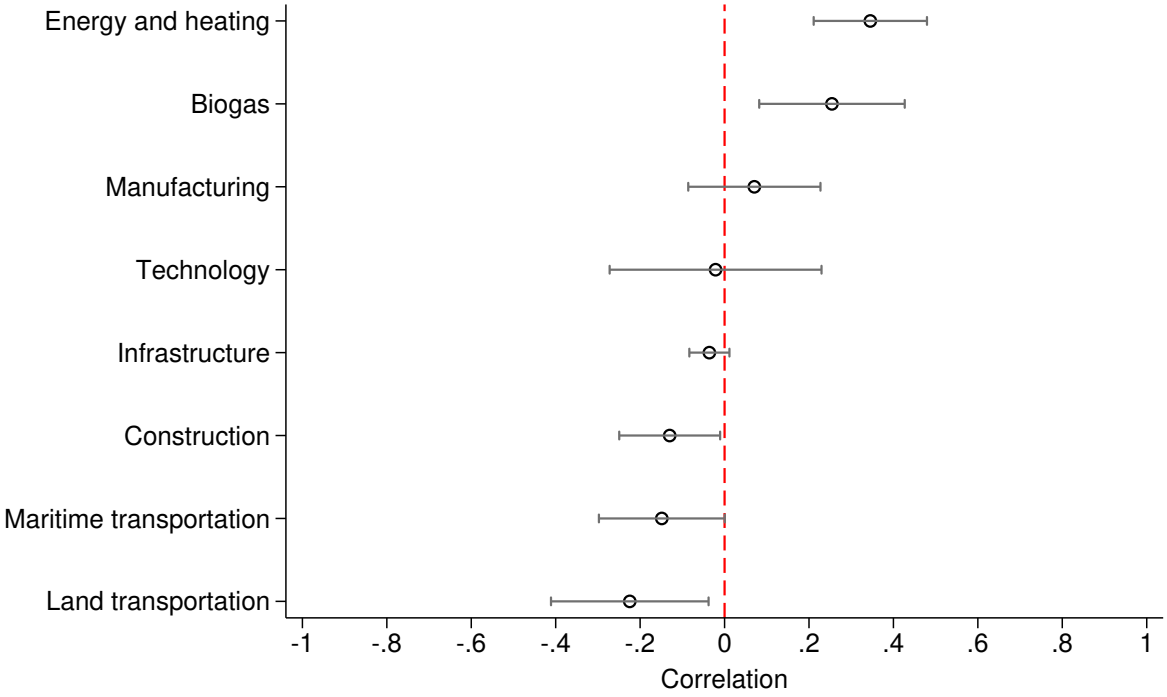


Figure 8. Correlates of misallocation on the margin. The figure shows the correlation between each topic area and the expected marginal return relative to the alternative policy, $\frac{\mathcal{E}[\Delta|r,q_r]}{c(r,q_r)} - \Delta_0$. For each characteristic on the y-axis, the dot reports the correlation coefficient and the horizontal bar shows the 95% confidence interval.

F. Sensitivity analyses

Extrapolation. As explained in Section IV, we observe expected and realized carbon emission returns for the full portfolio of Enova projects, which allows us to test for and bound misallocation. However, we do not observe the counterfactual returns of rejected Enova projects, which we need to point-identify misallocation. Following Cingano et al. (2025), we address this issue by extrapolating

expected and realized returns from marginally accepted to rejected projects. In Section IV, we show that our extrapolation performs well when applied to stated returns reported by firms in their applications, which are observed for all Enova projects, including rejected ones.

Additionally, in Appendix Table A.II, we explore the sensitivity of our point estimates along two dimensions: (i) restricting the bandwidth of the extrapolation and (ii) artificially increasing the slope of the extrapolation. Limiting the bandwidth constrains the extent of reallocation the decision-maker can implement, leading to more conservative estimates. Nonetheless, across all specifications in Table A.II, we continue to find substantial misallocation. For example, in our most conservative specification, where the decision-maker is only allowed to reallocate 40% of the optimal, we obtain an estimate of M at 0.019 tons of CO_2 per Euro, corresponding to about 35% of average returns on Enova projects. In the bottom rows of Table A.II, we find that increasing the slope on the extrapolation by a stringent 50% has no material impact on our estimates.

Alternative benchmark returns. In Table III, we bound and estimate misallocation by comparing the emission returns of Enova projects to the returns that could have been achieved by buying and deleting emission quotas in the EU ETS. In the second row of Appendix Table A.III, we reconstruct our lower bound estimate of M using an alternative climate policy benchmark; subsidies for preventing deforestation in the Amazon. Since the alternative benchmarks yield higher returns than the EU ETS, they lead to even larger lower bound estimates of misallocation. Naturally, point and upper bound estimates are also higher under these alternative benchmarks.

G. Robustness to unmeasured carbon emission effects

When testing for and measuring misallocation, we use project-level carbon emission returns reported by Enova. These returns are intended to capture all direct effects of the project on carbon emissions as measured by Enova. However, projects may impact carbon emissions in ways that are *not* measured by Enova, such as spillover effects on other firms. As explained in Section II.B, Enova is permitted to consider such unmeasured indirect emission effects for a subset of program areas,

constituting around 10% of our sample. For the remaining program areas, constituting around 90% of our sample, Enova only considers the direct carbon emission effects, which are captured in our data. One concern is that our estimates of misallocation may be capturing differences in how the decision-maker weights indirect carbon emission effects unobserved in our data.

As a first step to address this concern, we leverage the fact that for each program area, we know the weight the decision-maker assigns to indirect carbon emission effects. Specifically, when ranking projects, the decision-maker applies weights $1-\omega$ and ω to measured (direct) and unmeasured (indirect) emission effects. These weights are pre-specified, fixed, and known to all applicants when they apply for funding. In the third row of Appendix Table A.III, we reconstruct our lower bound on total misallocation, excluding the programs that consider unmeasured carbon emission effects when ranking projects, i.e., those with $\omega > 0$. To account for differences in total spending across samples, we report misallocation in terms of emission reductions per subsidy cost. We find no meaningful differences in misallocation between the full and restricted samples, suggesting that measurement error in emission returns does not materially impact our results.

As a second step, we assess how large unmeasured carbon emission effects would need to be to eliminate misallocation. In Appendix Figure A.2, we reconstruct our lower bound on misallocation while allowing for unmeasured effects that are proportional to the measured effects. Specifically, for accepted projects in program areas with $\omega > 0$, we replace the observed return $\frac{\Delta(r,q_r)}{c(r,q_r)}$ with $\Delta^* \equiv \frac{\Delta(r,q_r)}{c(r,q_r)}(1+\tau)$, where τ is varied across specifications. In practice, increasing the value of τ involves tilting upward the orange line in Figure 7. We find that unmeasured effects would need to be $\tau = 26$ times larger than measured effects to drive the lower bound on total misallocation to zero. We note that this exercise does not incorporate any unmeasured effects in the EU ETS, which would further increase the value, τ, required to drive the lower bound to zero.

A possible concern with the above robustness check is that there might be measurement error in ω. For example, it could be that some of the program areas that we classify as having an ω of zero actually consider unmeasured (indirect) emission effects when ranking projects. An extreme

robustness check would be to assume that *all* programs — including those that we classify as having an ω of zero — have an ω equal to 0.3 (the average ω across programs with positive ω). In this extreme scenario, we find that unmeasured effects would still need to be six times larger than measured effects to obtain a zero lower bound on total misallocation.

VI. Conclusion

We test for and measure misallocation of public subsidies for green investment projects. The context is a major green investment subsidy program in Norway over the period 2012–2023. Combining a model of subsidy allocation with detailed project-level data on carbon emissions and subsidy amounts for both marginal and inframarginal climate projects, we find that decision-makers could have achieved the same level of emission reductions at less than half the cost. To isolate the sources of this misallocation, we leverage unique data on both ex-ante expected and ex-post realized emission reductions for each project. We find that decision-makers are able ex-ante to identify the projects with the highest ex-post emission reductions, but unwilling to select them.

Our findings are of relevance to both policymakers and researchers. The process of allocating subsidies in Enova is organized around specialized programs. Most of these programs are targeted at specific mature green technologies. This specialization may help explain why the caseworkers are able to allocate subsidies within a program to the projects with relatively high investment additionality and carbon emission effects. However, the specialization may come at a cost: without proper coordination, the threshold for funding will vary between programs, resulting in heterogeneity in marginal returns and misallocation of funds. This problem can be addressed by setting a common minimum rate of return that all caseworkers need to expect from an investment. The minimum return should reflect the opportunity cost of the funds, such as the payoff to an alternative green policy.

Our paper also offers a blueprint for researchers to empirically analyze misallocation of government subsidies. We show the importance of focusing on marginal, rather than average, returns

when testing for misallocation, and the need for inframarginal returns to measure misallocation. We also show how to construct informative bounds on misallocation in settings where point identification is not feasible. Both our bounds and point estimates contrast with much of the existing climate literature, surveyed by Hahn et al. (2024), which tends to conflate average and marginal outcomes when assessing efficiency of climate policies.

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Appendix

Section I. Derivations and proofs **1**

Section II. Appendix Tables **14**

Section III. Appendix Figures **17**

I. Derivations and proofs

A. *Derivations: Sources of misallocation*

Here, we decompose total misallocation, M, into components that isolate the contribution from other motives and prediction errors. To do so, we first add and subtract the second-best allocation in equation (12) from our measure of misallocation in equation (10):

$$M = \overbrace{\underbrace{\sum_r \int_{f_r^c}^1 \frac{\Delta(r,f_r)}{c(r,f_r)} df_r + b_0^f \Delta_0}_{\text{First best: Realized return}} - \underbrace{\sum_r \int_{q_r^s}^1 \frac{\Delta(r,q_r)}{c(r,q_r)} dq_r + b_0^s \Delta_0}_{\text{Second best: Realized return}}}^{\text{Ranking error } M_r} +$$
$$\underbrace{\sum_r \int_{q_r^s}^1 \frac{\Delta(r,q_r)}{c(r,q_r)} dq_r + b_0^s \Delta_0}_{\text{Second best: Realized return}} - \underbrace{\sum_r \int_{q_r^c}^1 \frac{\Delta(r,q_r)}{c(r,q_r)} dq_r + b_0 \Delta_0}_{\text{Actual: Realized return}}.$$

Collecting terms, we have that:

$$M = \underbrace{M_r}_{\text{Ranking error}} + \underbrace{\sum_r \int_{q_r^s}^1 \frac{\Delta(r,q_r)}{c(r,q_r)} dq_r + b_0^s \Delta_0}_{\text{Second best: Realized return}} - \underbrace{\sum_r \int_{q_r^c}^1 \frac{\Delta(r,q_r)}{c(r,q_r)} dq_r + b_0 \Delta_0}_{\text{Actual: Realized return}}.$$

Next, we use our definition of λ from equation (5) to express the second-best and actual allocations in terms of the decision-maker's ex-ante expected returns:

$$M = \underbrace{M_r}_{\text{Ranking error}} + \underbrace{\sum_r \int_{q_r^s}^1 \frac{\mathcal{E}[\Delta|r,q_r]}{c(r,q_r)} + \lambda(r,q_r)\, dq_r + b_0^s \Delta_0}_{\text{Second best: Realized return}} - \underbrace{\sum_r \int_{q_r^c}^1 \frac{\mathcal{E}[\Delta|r,q_r]}{c(r,q_r)} + \lambda(r,q_r) dq_r + b_0 \Delta_0}_{\text{Actual: Realized return}}.$$

Rearranging, we have that:

$$= \underbrace{M_r}_{\text{Ranking error}} + \overbrace{\sum_r \left(\underbrace{\int_{q_r^s}^1 \lambda(r, q_r)\, dq_r}_{\text{Second best: Realization error}} - \underbrace{\int_{q_r^c}^1 \lambda(r, q_r)\, dq_r}_{\text{Actual: Realization error}} \right)}^{\text{Realization error: } \Lambda} +$$

$$\overbrace{\underbrace{\sum_r \int_{q_r^s}^1 \frac{\mathcal{E}[\Delta|r, q_r]}{c(r, q_r)}\, dq_r + b_0^s \Delta_0}_{\text{Second best: Expected return}} - \underbrace{\sum_r \int_{q_r^c}^1 \frac{\mathcal{E}[\Delta|r, q_r]}{c(r, q_r)} dq_r + b_0 \Delta_0}_{\text{Actual: Expected return}}}^{\text{Other motives: } M_\beta}.$$

Main expression. Accordingly, we can express total misallocation as:

$$\underbrace{M}_{\text{Misallocation}} = \underbrace{M_\beta}_{\text{Other motives}} + \overbrace{\underbrace{M_r}_{\text{Ranking error}} + \underbrace{\Lambda}_{\text{Realization error}}}^{\text{Prediction errors}}.$$

B. *Derivations: Sources and margins of misallocation*

Here, we decompose misallocation, M, into components that capture both the sources and margins of misallocation. To do so, we first define a second-best autarky allocation, analogous to the first-best autarky allocation in equation (15), but where the decision-maker selects projects based on ex-ante rather than ex-post returns. Let q_r^A denote the marginally accepted Enova projects in this second-best autarky allocation, where expected ex-ante returns are equalized across programs. The total realized return under the second-best autarky allocation is then given by:

$$\sum_r \int_{q_r^A}^{1} \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r \tag{A.1}$$

Next, we define a second-best overspending component:

$$\sum_r \int_{q_r^A}^{q_r^s} \Delta_0 - \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r. \tag{A.2}$$

Adding and subtracting equation (A.2) from equation (16), we get:

$$\begin{aligned} M = & \underbrace{\left(\sum_r \int_{f_r^A}^{f_r^c} \left(\Delta_0 - \frac{\Delta(r, f_r)}{c(r, f_r)} \right) df_r - \sum_r \int_{q_r^A}^{q_r^s} \left(\Delta_0 - \frac{\Delta(r, q_r)}{c(r, q_r)} \right) dq_r \right)}_{\text{Overspending due to ranking errors: } M_r^O} \\ & + \underbrace{\left(\sum_r \int_{f_r^A}^{1} \frac{\Delta(r, f_r)}{c(r, f_r)} df_r - \sum_r \int_{q_r^c}^{1} \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r \right)}_{\text{Misspending within Enova: } M^S} + \sum_r \int_{q_r^A}^{q_r^s} \left(\Delta_0 - \frac{\Delta(r, q_r)}{c(r, q_r)} \right) dq_r - b_0 \Delta_0. \end{aligned} \tag{A.3}$$

Adding and subtracting equation (A.1) from equation (A.3), we get:

$$\begin{aligned} M =& M_r^O + \underbrace{\left(\sum_r \int_{f_r^A}^1 \frac{\Delta(r, f_r)}{c(r, f_r)} df_r - \int_{q_r^A}^1 \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r \right)}_{\text{Misspending due to ranking errors: } M_r^S} \\ &+ \sum_r \int_{q_r^A}^{q_r^s} \Delta_0 - \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r + \sum_r \int_{q_r^A}^1 \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r - \int_{q_r^c}^1 \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r - b_0 \Delta_0 \\ =& M_r^O + M_r^S + \sum_r \int_{q_r^A}^{q_r^s} \Delta_0 - \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r + \sum_r \int_{q_r^A}^1 \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r - \int_{q_r^c}^1 \frac{\Delta(r, q_r)}{c(r, q_r)} dq_r - b_0 \Delta_0. \end{aligned}$$

Using our definition of λ from equation (5), we have that:

$$\begin{aligned} M =& M_r^O + M_r^S + \sum_r \int_{q_r^A}^{q_r^s} \Delta_0 - \frac{\mathcal{E}[\Delta \mid r, q_r]}{c(r, q_r)} - \lambda(r, q_r)\, dq_r + \sum_r \int_{q_r^A}^1 \frac{\mathcal{E}[\Delta \mid r, q_r]}{c(r, q_r)} + \lambda(r, q_r) dq_r \\ &- \int_{q_r^c}^1 \frac{\mathcal{E}[\Delta \mid r, q_r]}{c(r, q_r)} + \lambda(r, q_r) dq_r - b_0 \Delta_0. \end{aligned}$$

Rearranging and collecting terms, we have that:

$$\begin{aligned} =& M_r^O + M_r^S + \underbrace{\sum_r \int_{q_r^A}^{q_r^s} \Delta_0 - \frac{\mathcal{E}[\Delta \mid r, q_r]}{c(r, q_r)}\, dq_r - b_0 \Delta_0}_{\text{Overspending due to other motives: } M_\beta^O} + \underbrace{\sum_r \int_{q_r^A}^1 \frac{\mathcal{E}[\Delta \mid r, q_r]}{c(r, q_r)} dq_r - \int_{q_r^c}^1 \frac{\mathcal{E}[\Delta \mid r, q_r]}{c(r, q_r)} dq_r}_{\text{Misspending due to other motives: } M_\beta^S} \\ &+ \underbrace{\sum_r \int_{q_r^A}^{q_r^s} -\lambda(r, q_r) dq_r}_{\text{Realization errors for overspending: } \Lambda^O} + \underbrace{\sum_r \int_{q_r^A}^1 \lambda(r, q_r) dq_r - \sum_r \int_{q_r^c}^1 \lambda(r, q_r) dq_r}_{\text{Realization error for misspending: } \Lambda^S}. \end{aligned}$$

Main expression. Accordingly, we can express total misallocation as:

$$M = \underbrace{M_r^O + M_\beta^O + \Lambda^O}_{\text{Overspending on Enova: } M^O} + \underbrace{M_r^S + M_\beta^S + \Lambda^S}_{\text{Misspending within Enova: } M^S}.$$

C. *Proof: Lemma 1*

Here, we show that misallocation, M, can be expressed as the sum of lost realized returns due to Type I (wrongly rejected projects) and Type II errors (wrongly accepted projects). First, we note that M from (10) can be expressed in terms of total emission effects over total costs:

$$M = \underbrace{\sum_r \frac{1}{\bar{B}} \int_{f_r^c}^1 \Delta(r, f_r) df_r + b_0^f \Delta_0}_{\text{First best allocation}} \quad - \quad \underbrace{\sum_r \frac{1}{\bar{B}} \int_{q_r^c}^1 \Delta(r, q_r) dq_r + b_0 \Delta_0}_{\text{Actual allocation}}. \tag{A.4}$$

Using the selection equations (6) and (8), we can rewrite equation (A.4) as:

$$M = \underbrace{\sum_r \frac{1}{\bar{B}} \int_0^1 \tilde{D} * \Delta(r, f_r) df_r + b_0^f \Delta_0}_{\text{First best allocation}} \quad - \quad \underbrace{\sum_r \frac{1}{\bar{B}} \int_0^1 D * \Delta(r, f_r) df_r + b_0 \Delta_0}_{\text{Actual allocation}} \tag{A.5}$$

$$= \sum_r \frac{1}{\bar{B}} \int_0^1 (\tilde{D} - D) * \Delta(r, f_r) \; df_r + \Delta_0 (b_0^f - b_0). \tag{A.6}$$

Next, both the first-best and actual allocations must satisfy the budget constraint $\bar{B}$:

$$\bar{B} = \underbrace{\sum_r \int_0^1 D \, c(r, f_r) \, df_r + \bar{B} b_0}_{\text{Actual allocation: Spending}} = \underbrace{\sum_r \int_0^1 \tilde{D} \, c(r, f_r) \, df_r + \bar{B} b_0^f}_{\text{First best: Spending}}. \tag{A.7}$$

Using this equality, it follows that:

$$(b_0^f - b_0) = \sum_r \frac{1}{\bar{B}} \int_0^1 (D - \tilde{D}) \, c(r, f_r) \, df_r.$$

Inserting this expression into equation (A.5), we get:

$$
\begin{aligned}
M &= \sum_r \frac{1}{\bar{B}} \int_0^1 (\tilde{D} - D) * \Delta(r, f_r)\ df_r + \sum_r \frac{1}{\bar{B}} \int_0^1 (D - \tilde{D}) \Delta_0\, c(r, f_r)\, df_r \\
&= \sum_r \frac{1}{\bar{B}} \int_0^1 (\tilde{D} - D) \left(\frac{\Delta(r, f_r)}{c(r, f_r)} - \Delta_0 \right) c(r, f_r)\ df_r \\
&= \sum_r \frac{1}{\bar{B}} \int_0^1 \underbrace{\mathbb{I}[\tilde{D} > D] \left(\frac{\Delta(r, f_r)}{c(r, f_r)} - \Delta_0 \right) c(r, f_r)}_{\text{Type I: Wrongly rejected projects}} + \underbrace{\mathbb{I}[\tilde{D} < D] \left(\Delta_0 - \frac{\Delta(r, f_r)}{c(r, f_r)} \right) c(r, f_r)}_{\text{Type II: Wrongly accepted projects}}\ df_r.
\end{aligned}
$$

□

D. *Proof: Proposition 1b*

Here, we show that we can construct an informative upper bound on M by using information about the average realized return of correctly accepted projects, the average subsidy cost of rejected projects, and the prevalence of rejected projects. We start by repeating Lemma 1:

$$M = \sum_r \frac{1}{\bar{B}} \int_0^1 \underbrace{\mathbb{I}[\tilde{D} > D]\left(\frac{\Delta(r, f_r)}{c(r, f_r)} - \Delta_0\right) c(r, f_r)}_{\text{Type I: Wrongly rejected projects}} + \underbrace{\mathbb{I}[\tilde{D} < D]\left(\Delta_0 - \frac{\Delta(r, f_r)}{c(r, f_r)}\right) c(r, f_r)}_{\text{Type II: Wrongly accepted projects}} \, df_r \quad \text{(A.8)}$$

From Proposition 1a, the second term forms a worst-case lower bound, M^{LB}, on total misallocation, M. To construct an upper bound on M, we make assumptions about the Type I errors in equation (A.8). First, we rewrite the Type I term of the equation (A.8) as:

$$\overbrace{\sum_r \frac{1}{\bar{B}} \mathbb{P}[\tilde{D} = 1 \cap D = 0 \mid r]\Big(\mathbb{E}[\Delta \mid r, \tilde{D} = 1, D = 0] - \Delta_0 \mathbb{E}[c \mid r, \tilde{D} = 1, D = 0]\Big)}^{\text{Type I: Wrongly rejected projects}} =$$
$$\sum_r \frac{1}{\bar{B}} \mathbb{P}[\tilde{D} = 1 \cap D = 0 \mid r] * \mathbb{E}[c \mid r, \tilde{D} = 1, D = 0]\left(\frac{\mathbb{E}[\Delta \mid r, \tilde{D} = 1, D = 0]}{\mathbb{E}[c \mid r, \tilde{D} = 1, D = 0]} - \Delta_0\right)$$

The share of wrongly rejected projects cannot exceed the *total* share of rejected projects, which means that $\mathbb{P}[\tilde{D} = 1 \cap D = 0 \mid r] \leq \mathbb{P}(D = 0 \mid r)$. In that case, we would have $\mathbb{P}[\tilde{D} = 1 \cap D = 0 \mid r] = \mathbb{P}(D = 0 \mid r)$ and $\mathbb{E}[c \mid r, \tilde{D} = 1, D = 0] = \mathbb{E}[c \mid r, D = 0]$. The law of total expectation implies that:

$$\overbrace{\sum_r \frac{1}{\bar{B}} \mathbb{P}[\tilde{D} = 1 \cap D = 0 \mid r] * \mathbb{E}[c \mid r, \tilde{D} = 1, D = 0]\left(\frac{\mathbb{E}[\Delta \mid r, \tilde{D} = 1, D = 0]}{\mathbb{E}[c \mid r, \tilde{D} = 1, D = 0]} - \Delta_0\right)}^{\text{Type I Wrongly rejected projects}}$$
$$\leq \sum_r \frac{1}{\bar{B}} \mathbb{P}[D = 0 \mid r] * \mathbb{E}[c \mid r, D = 0]\left(\frac{\mathbb{E}[\Delta \mid r, \tilde{D} = 1, D = 0]}{\mathbb{E}[c \mid r, \tilde{D} = 1, D = 0]} - \Delta_0\right).$$

Under Assumption 1, it further follows that:

$$\sum_r \frac{1}{\bar{\bar{B}}} \underbrace{\mathbb{P}[D=0 \mid r]}_{\text{Prevalence of rejected projects}} * \underbrace{\mathbb{E}[c \mid r, D=0]}_{\text{Cost of rejected projects}} \underbrace{\left(\frac{\mathbb{E}[\Delta \mid r, \tilde{D}=1, D=0]}{\mathbb{E}[c \mid r, \tilde{D}=1, D=0]} - \Delta_0 \right)}_{\text{Return on wrongly rejected projects}}$$

$$\leq \sum_r \frac{1}{\bar{\bar{B}}} \underbrace{\mathbb{P}[D=0 \mid r]}_{\text{Prevalence of rejected projects}} * \underbrace{\mathbb{E}[c \mid r, D=0]}_{\text{Cost of rejected projects}} \underbrace{\left(\frac{\mathbb{E}[\Delta \mid r, \tilde{D}=1, D=1]}{\mathbb{E}[c \mid r, \tilde{D}=1, D=1]} - \Delta_0 \right)}_{\text{Return on correctly accepted projects}}.$$

so that:

$$M \leq \underbrace{\sum_r \frac{1}{\bar{B}} \left(\frac{\mathbb{E}[\Delta \mid r, \tilde{D}=1, D=1]}{\mathbb{E}[c \mid r, \tilde{D}=1, D=1]} - \Delta_0 \right) \mathbb{P}[D=0 \mid r] \mathbb{E}[c \mid r, D=0]}_{\text{Upper bound on Type I: Wrongly rejected projects}} + M^{\text{TypeII}}.$$

where all terms are observed in the data. □

E. *Proof: Lemma 3*

Here, we show that M_β can be expressed as the total loss in expected carbon emission returns due to ex-ante Type I errors and ex-ante Type II errors. To do so, we first note that M_β can be expressed in terms of total expected carbon emission effects over total costs:

$$M_\beta = \underbrace{\sum_r \frac{1}{\bar{B}} \int_{q_r^s}^1 \mathcal{E}(\Delta|r, q_r) dq_r + b_0^s \Delta_0}_{\text{Second best: Expected returns}} \quad - \quad \underbrace{\sum_r \frac{1}{\bar{B}} \int_{q_r^c}^1 \mathcal{E}(\Delta \mid r, q_r) dq_r + b_0 \Delta_0}_{\text{Actual: Expected returns}}. \tag{A.9}$$

Using the selection equations (6) and (11), we can rewrite equation (A.9) as:

$$M_\beta = \underbrace{\sum_r \frac{1}{\bar{B}} \int_0^1 D^{SB} * \mathcal{E}(\Delta \mid r, q_r) dq_r + b_0^s \Delta_0}_{\text{Second best: Expected returns}} \quad - \quad \underbrace{\sum_r \frac{1}{\bar{B}} \int_0^1 D * \mathcal{E}(\Delta \mid r, q_r) dq_r + b_0 \Delta_0}_{\text{Actual: Expected returns}} \tag{A.10}$$

$$= \sum_r \frac{1}{\bar{B}} \int_0^1 (D^{SB} - D) * \mathcal{E}(\Delta \mid r, q_r) dq_r \; + \Delta_0 (b_0^s - b_0). \tag{A.11}$$

Next, both the first-best and actual allocations must satisfy the budget constraint $\bar{B}$:

$$\bar{B} = \underbrace{\sum_r \int_0^1 D\, c(r, q_r)\, dq_r + \bar{B} b_0}_{\text{Actual allocation: Spending}} = \underbrace{\sum_r \int_0^1 D^{SB}\, c(r, q_r)\, dq_r + \bar{B} b_0^s}_{\text{Second best: Spending}}. \tag{A.12}$$

Using this equality, it follows that:

$$(b_0^s - b_0) = \sum_r \frac{1}{\bar{B}} \int_0^1 (D - D^{SB})\, c(r, q_r)\, dq_r.$$

Inserting this expression into equation (A.11), we get:

$$
\begin{aligned}
M_\beta &= \sum_r \frac{1}{\overline{B}} \int_0^1 (D^{SB} - D) * \mathcal{E}(\Delta \mid r, q_r) dq_r + \sum_r \frac{1}{\overline{B}} \int_0^1 (D - D^{SB}) \Delta_0 \, c(r, q_r) \, dq_r \\
&= \sum_r \frac{1}{\overline{B}} \int_0^1 (D^{SB} - D) \left(\frac{\mathcal{E}(\Delta \mid r, q_r)}{c(r, q_r)} - \Delta_0 \right) c(r, q_r) \; dq_r \\
&= \sum_r \frac{1}{\overline{B}} \int_0^1 \underbrace{\mathbb{I}[D^{SB} > D] \left(\frac{\mathcal{E}[\Delta | r, q_r]}{c(r, q_r)} - \Delta_0 \right) c(r, q_r)}_{\text{Type I: Ex-ante wrongly rejected projects}} + \underbrace{\mathbb{I}[D^{SB} < D] \left(\Delta_0 - \frac{\mathcal{E}[\Delta | r, q_r]}{c(r, q_r)} \right) c(r, q_r)}_{\text{Type II: Ex-ante wrongly accepted projects}} \quad dq_r .
\end{aligned}
$$

□

F. *Proof: Proposition 2b*

Here, we show that we can construct an upper bound on M_β by using information about the average return of ex-ante correctly accepted projects, the average subsidy cost of rejected projects, and the prevalence of rejected projects. We start by repeating Lemma 3:

$$M_\beta = \sum_r \frac{1}{\bar{B}} \int_0^1 \underbrace{\mathbb{I}[D^{SB} > D]\left(\frac{\mathcal{E}[\Delta|r,q_r]}{c(r,q_r)} - \Delta_0\right) c(r,q_r)}_{\text{Type I: Ex-ante wrongly rejected projects}} + \underbrace{\mathbb{I}[D^{SB} < D]\left(\Delta_0 - \frac{\mathcal{E}[\Delta|r,q_r]}{c(r,q_r)}\right) c(r,q_r)}_{\text{Type II: Ex-ante wrongly accepted projects}} dq_r. \tag{A.13}$$

From Proposition 2a, the second term forms a worst-case lower bound, M_β^{LB}, on total misallocation due to other motives, M_β. To construct an upper bound on M_β, we make assumptions about the Type I errors in equation (A.13). We begin by rewriting the Type I term as:

$$\overbrace{\sum_r \frac{1}{\bar{B}} \left(\underbrace{\frac{\mathbb{E}\left[\mathcal{E}[\Delta] \mid r, D^{SB}=1, D=0\right]}{\mathbb{E}\left[c \mid r, D^{SB}=1, D=0\right]} - \Delta_0}_{\text{Return on ex-ante wrongly rejected projects}}\right) \underbrace{\mathbb{E}[c \mid r, D^{SB}=1, D=0]}_{\text{... their cost}} * \underbrace{P[D^{SB}=1 \cap D=0 \mid r]}_{\text{... and their prevalence}}}^{\text{Type I: Ex-ante wrongly rejected projects}}.$$

The share of ex-ante wrongly rejected projects cannot exceed the *total* share of rejected projects, which means that $\mathbb{P}[D^{SB}=1 \cap D=0 \mid r] \leq \mathbb{P}(D=0 \mid r)$. Under the (worst case) scenario in which all ex-ante rejected projects are wrongly rejected, we have that $\mathbb{P}[D^{SB}=1 \cap D=0 \mid r] =$

$\mathbb{P}(D=0 \mid r)$ and $\mathbb{E}[c \mid r, D^{SB}=1, D=0] = \mathbb{E}[c \mid r, D=0]$. This implies that:

$$\overbrace{\sum_r \frac{1}{\overline{B}} \Bigg(\underbrace{\frac{\mathbb{E}\left[\mathcal{E}[\Delta] \mid r, D^{SB}=1, D=0\right]}{\mathbb{E}\left[c \mid r, D^{SB}=1, D=0\right]} - \Delta_0}_{\text{Return on ex-ante wrongly rejected projects}} \Bigg) * \underbrace{\mathbb{E}[c \mid r, D^{SB}=1, D=0]}_{\text{... their cost}} * \underbrace{\mathbb{P}[D^{SB}=1 \cap D=0 \mid r]}_{\text{... and their prevalence}}}^{\text{Type I: Ex-ante wrongly rejected projects}}$$

$$\leq \sum_r \frac{1}{\overline{B}} \Bigg(\underbrace{\frac{\mathbb{E}\left[\mathcal{E}[\Delta] \mid r, D^{SB}=1, D=0\right]}{\mathbb{E}\left[c \mid r, D^{SB}=1, D=0\right]} - \Delta_0}_{\text{Return on ex-ante wrongly rejected projects}} \Bigg) * \underbrace{\mathbb{E}[c \mid r, D=0]}_{\text{Cost of rejected projects}} * \underbrace{\mathbb{P}[D=0 \mid r]}_{\text{Prevalence of rejected projects}}.$$

Under Assumption 2, it further follows that:

$$\overbrace{\sum_r \frac{1}{\overline{B}} \Bigg(\underbrace{\frac{\mathbb{E}\left[\mathcal{E}[\Delta] \mid r, D^{SB}=1, D=0\right]}{\mathbb{E}\left[c \mid r, D^{SB}=1, D=0\right]} - \Delta_0}_{\text{Return on ex-ante wrongly rejected projects}} \Bigg) * \underbrace{\mathbb{E}[c \mid r, D^{SB}=1, D=0]}_{\text{Cost}} * \underbrace{\mathbb{P}[D^{SB}=1 \cap D=0 \mid r]}_{\text{Prevalence}}}^{\text{Type I: Ex-ante wrongly rejected projects}}$$

$$\leq \overbrace{\sum_r \frac{1}{\overline{B}} \Bigg(\underbrace{\frac{\mathbb{E}\left[\mathcal{E}[\Delta] \mid r, D^{SB}=1, D=1\right]}{\mathbb{E}\left[c \mid r, D^{SB}=1, D=1\right]} - \Delta_0}_{\text{Return on correctly accepted projects}} \Bigg) * \underbrace{\mathbb{E}[c \mid r, D=0]}_{\text{Cost of rejected projects}} * \underbrace{\mathbb{P}[D=0 \mid r]}_{\text{Prevalence of rejected projects}}}^{\text{Observed}},$$

so that:

$$M_\beta \leq \underbrace{\sum_r \frac{1}{\overline{B}} \left(\frac{\mathbb{E}\left[\mathcal{E}[\Delta] \mid r, D^{SB}=1, D=1\right]}{\mathbb{E}\left[c \mid r, D^{SB}=1, D=1\right]} - \Delta_0 \right) \mathbb{E}[c \mid r, D=0]\, \mathbb{P}[D=0 \mid r]}_{\text{Upper bound on Type I: Ex-ante wrongly rejected projects}} + M_\beta^{\text{TypeII}},$$

where all terms are observed in the data. □

G. Proof: Lower bound with partial investment additionality

Let $\Delta \equiv Y(1)-Y(0)$ denote a project's carbon emission effect, where $Y(1)$ represents emissions with the subsidy and promised investment, and $Y(0)$ represents emissions without, and $Y(1) > Y(0)$. We now show that the lower bound we estimate is valid for all values of $0 \leq Y(0) \leq Y(1)$.

Consider first the case of full additionality ($Y(0) = 0$). The lower bound on M becomes:

$$M^{LB} = \sum_r \frac{1}{\bar{B}} \int_0^1 I[\tilde{D} < D] \left(\Delta_0 - \frac{Y_1(r, f_r)}{c(r, f_r)} \right) c(r, f_r) \; df_r.$$

Consider next the case with partial or no investment additionality ($0 < Y(0) \leq Y(1)$). The lower bound on M is then:

$$\tilde{M}^{LB} = \sum_r \frac{1}{\bar{B}} \int_0^1 I[\tilde{D} < D] \left(\Delta_0 - \frac{Y_1(r, f_r) - Y_0(r, f_r)}{c(r, f_r)} \right) c(r, f_r) \; df_r.$$

When $Y(0) > 0$ for some, or all, firms, it follows that:

$$M^{LB} \; < \; \tilde{M}^{LB}.$$

□

II. Appendix Tables

Table A.I. List of program areas active between 2012 and 2023

	Means		
Program area	c	$\mathcal{E}(\Delta)$	Δ
Topic: Biogas and biofuel			
Biogas and Biofuels	2571.6	245634.7	245297.4
Topic: Energy systems and heating			
District Heating and Cooling	384.5	33267.4	31650.8
Extended Heating Plants	15.6	1286.1	768.9
Heating Plants	20.1	2256.8	2215.6
Simplified Heating Plants	3.9	550.0	498.7
Topic: Manufacturing			
Energy and Climate Initiatives in Industry	89.6	8008.1	8082.6
Energy and Climate Measures in Industry and Construction	206.4	14847.5	14841.0
Support for New Energy and Climate Technology in Industry	2158.4	75675.7	47560.9
Topic: Buildings and construction			
Energy-Efficient New Buildings	598.2	7219.0	6905.5
Existing Buildings	88.9	7554.9	6703.4
Introduction of New Technology in Buildings and Areas	388.8	4475.4	3193.8
New Technology for Future Buildings	85.9	625.2	180.4
Support for Energy Measures in Facilities	228.4	18029.6	21054.2
Support for Existing Buildings	185.3	17579.3	14511.9
Support for Existing Buildings and Facilities	643.1	88056.5	65356.8
Zero-emission Construction Machines	18.3	126.0	126.0
Topic: Infrastructure and facilitation			
Infrastructure for Municipal and County Transport Services	1333.2	54084.3	45593.4
Topic: Technology development and innovation			
Commercial Piloting	188.9	5200.7	4638.5
Demonstration of New Energy and Climate Technology	183.7	4308.6	4049.4
Full-Scale Innovative Energy and Climate Technology	1655.6	76546.6	74305.5
Support for Introduction of New Technology	171.4	2514.3	2254.2
Topic: Land transportation			
Energy and Climate Measures in Land Transport	150.2	1904.0	1904.0
Heavy Vehicles	181.8	1444.3	1425.5
Support for New Energy and Climate Technology in Transport	1356.1	13382.4	23500.4
Zero-Emission Fund Electric Vans	5.0	306.3	240.4
Topic: Maritime transportation			
Batteries in Vessels	487.3	6519.2	6561.5
Electrification of Maritime Transport	845.0	20468.0	20125.2
Energy and Climate Measures in Shipping	452.4	22292.5	22511.5
Investment Support for Shore Power and Charging Infrastructure	416.3	8554.5	8554.5

Notes: The table provides an overview of Enova program areas active over the period 2012–2023. We restrict attention to the program areas represented in our main estimation sample described in Section II.B. The subsidy amount, c, is expressed in 1000 EUR, while the carbon emission effects ($\mathcal{E}(\Delta)$, Δ) are expressed in tons of CO_2.

Table A.II. Sensitivity of the point estimates: Bandwidth and slope

		Sources			Margins	
	M	M_β	M_r	Λ	M^O	M^S
Baseline	0.052	0.050	0.001	0.001	0.047	0.005
Sensitivity to bandwidth						
$Bandwidth = 40$	0.019	0.020	0.000	-0.001	0.015	0.004
$Bandwidth = 60$	0.031	0.028	0.002	0.001	0.026	0.005
$Bandwidth = 80$	0.041	0.035	0.002	0.004	0.036	0.005
$Bandwidth = 100$	0.052	0.050	0.001	0.001	0.047	0.005
Sensitivity to slope	0.052	0.049	0.002	0.001	0.048	0.004
Sensitivity to bandwidth and slope						
$Bandwidth = 40$	0.022	0.018	0.001	0.003	0.018	0.004
$Bandwidth = 60$	0.031	0.026	0.001	0.004	0.027	0.004
$Bandwidth = 80$	0.040	0.039	0.002	0.001	0.036	0.004
$Bandwidth = 100$	0.052	0.049	0.002	0.001	0.048	0.004

Notes: The first row reproduces our point estimate of total misallocation, M, its sources (M_β, M_r, Λ) and margins (M^O, M^S) from Table III–IV. Misallocation is measured in tons of CO_2 per Euro. Rows (2)–(5) examine the sensitivity of our estimates to the choice of bandwidth when extrapolating returns from accepted to rejected projects. A bandwidth of 40 means that only 40% of funds each year can be reallocated; a bandwidth of 100% means all funds can be reallocated. Row (6) examines sensitivity to steepening the slope of the extrapolation by 50%. Rows (7)–(10) examine sensitivity to both the choice of bandwidth and steepening the slope of the extrapolation by 50%.

Table A.III. Sensitivity of the lower bounds: Alternative policy, spillovers and discounting

		Sources		
	M	M_β	M_r	Λ
Baseline	0.051	0.046	0.000	$-\infty$
Sensitivity to alternative benchmark	0.122	0.118	0.000	$-\infty$
Sensitivity to unmeasured carbon emission effects	0.052	0.047	0.000	$-\infty$
Sensitivity to changing the discount rate: $r = 0\%$	0.045	0.041	0.000	$-\infty$
Sensitivity to changing the discount rate: $r = 4\%$	0.055	0.052	0.000	$-\infty$
Sensitivity to changing the discount rate: $r = 6\%$	0.059	0.056	0.000	$-\infty$

Notes: The first row reproduces our lower bound on total misallocation, M, and its sources (M_β, M_r, Λ) from Table III. Misallocation is measured in tons of CO_2 per Euro. Row (2) examines the sensitivity of our lower bound to using subsidies to prevent tropical deforestation as the decision-maker's alternative policy. Following Harding et al. (2021) and Assunção et al. (2023), we use \$6.5 per ton of CO_2 as the return to this policy. Row (3) examines sensitivity to excluding a small set of program areas that consider unmeasured emission effects when ranking projects. In the main analysis, all carbon emission effects are reported in present value terms using a 2% annual discount rate. Rows (4)–(6) examine the sensitivity of the estimates to instead applying a 0%, 4%, and 6% discount rate.

III. Appendix Figures

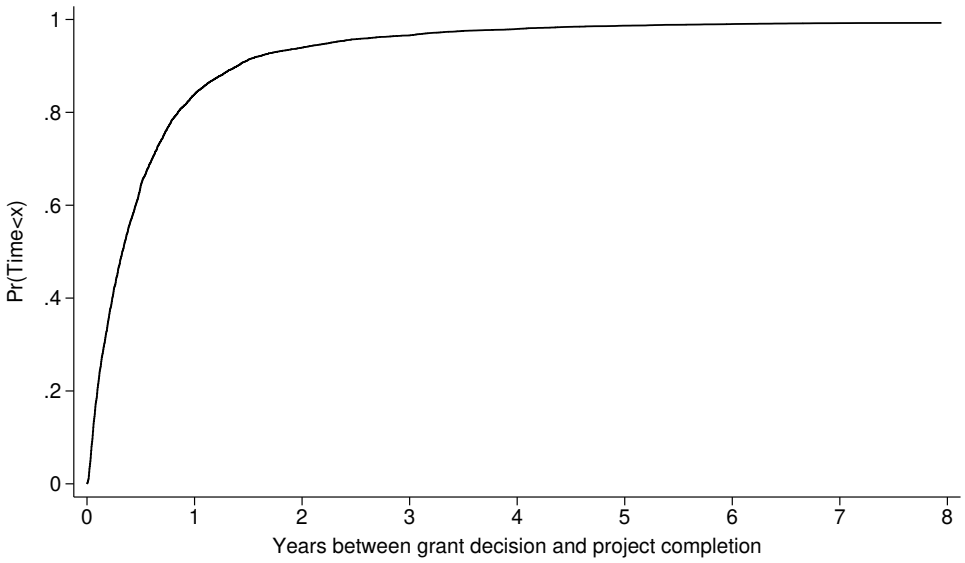


Figure A.1. Project completion. The figure shows the probability that a project is completed after a given number of years relative to the grant decision date. We measure completion using the date the project receives its final payment, as payment is contingent on verification that the investment has been made. The figure is based on a sample of projects accepted before 2020 that can be observed for at least four years.

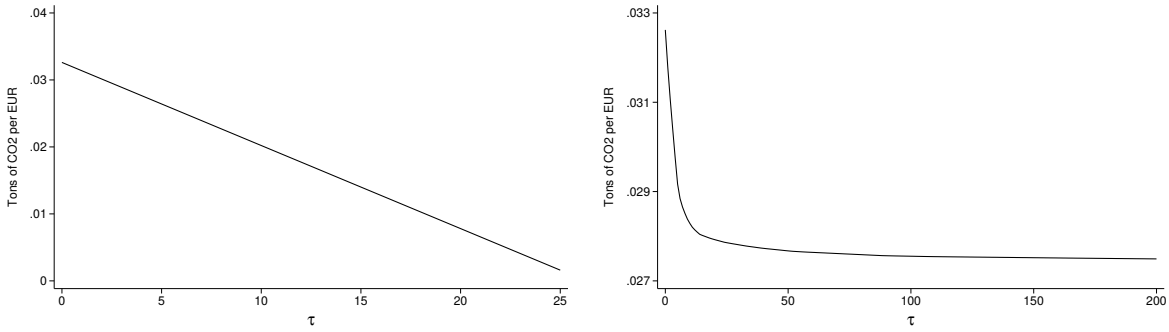


Figure A.2. Robustness to unmeasured carbon emission effects. In Panel A, we reconstruct our lower bound on misallocation from Proposition 1b while allowing for unmeasured carbon emission effects that are proportional to the measured carbon emission effects. Specifically, for accepted projects in program areas with that consider unmeasured carbon emission effects, we replace the observed return $\frac{\Delta(r,q_r)}{c(r,q_r)}$ with $\Delta^* \equiv \frac{\Delta(r,q_r)}{c(r,q_r)}(1+\tau)$, where τ is varied across specifications. In this exercise, we estimate τ for a fixed set of projects, namely, those determined to be wrongly accepted according to the baseline decision-maker's project selection rule in equation (6), which is based on observable carbon emission returns, $\frac{\Delta(r,q_r)}{c(r,q_r)}$. In Panel B, we present results from an alternative analysis where, in addition to replacing $\frac{\Delta(r,q_r)}{c(r,q_r)}$ with Δ^* when measuring returns, we also allow project selection to be based on Δ^*.