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GREEN WASTE

Ingvil Gaarder
Morten Grindaker
Tom G. Meling
Magne Mogstad

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ABSTRACT

We develop and apply a framework to test for and measure green waste: the misallocation of public subsidies for green investment projects. Our context is a major Norwegian subsidy program to reduce carbon emissions. We apply the framework to detailed project-level data on carbon emissions and subsidy amounts for both marginal and inframarginal projects. We find that the decision-maker 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 the decision-maker is able ex-ante to identify the projects with the highest ex-post emission reductions but unwilling to select them.

Ingvil Gaarder
The University of Chicago
ingvil.gaarder@gmail.com

Morten Grindaker
Statistics Norway
morten.grindaker@gmail.com

Tom G. Meling
The Ohio State University
tom.grimstvedt.meling@gmail.com

Magne Mogstad
The University of Chicago
Department of Economics
and NBER
magne.mogstad@gmail.com

I. Introduction

Governments worldwide use targeted investment subsidies to speed the adoption of green technologies and cut carbon emissions. 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, which is difficult for several reasons.[1] A key challenge is to appropriately define misallocation in a given setting. This requires properly specifying the decision-maker's objective, the constraints and opportunity costs she faces, and the information available at the time decisions are made. Once specified, the analyst can derive optimality conditions that equate the relevant marginal benefits and costs. Another key challenge is to measure these benefits and costs and check whether they are equated in the data. If not, there is misallocation, and the decision-maker could achieve higher returns by reallocating funds.

To address these challenges and answer the above questions, we will develop and apply a framework to test for and measure misallocation and to isolate its sources. The framework stresses the importance of focusing on marginal, rather than average, returns when testing for misallocation, and the need to observe inframarginal returns to measure misallocation and understand its sources. We also show how to construct informative bounds on misallocation in settings where the analyst does not perfectly observe the relevant returns. This measurement problem could arise from unmeasured spillover effects from subsidy recipients to non-recipients, or from difficulties in measuring counterfactual returns for subsidy non-recipients.

We apply the framework to the allocation of green investment subsidies in Norway over the period 2012–2023. We have access to detailed administrative data from the country's main program

[1] The review article of Low and Pistaferri (2025b) explains the conditions needed to test for discrimination and misallocation; see also Canay et al. (2023) and Heckman et al. (1998).

for green investment subsidies, which records project-level carbon emission reductions and subsidy amounts for all accepted projects. Combining these data with our framework allows us to test for and measure misallocation. We find that the decision-maker 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 expected and realized carbon emission reductions for each project. We find 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. We show that the conclusion about significant green waste is robust to allowing for large unmeasured spillover effects, and to assuming no Type I errors (wrongly rejected projects) so that the measured misallocation becomes a lower bound that only captures Type II errors (wrongly accepted projects).

In Section II, we describe 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. Enova's mandate is to reduce carbon emissions in private firms. This may be achieved in two ways: Directly, by reducing carbon emissions within the applicant firm, and indirectly, through spillover effects from the green investment in the applicant firm to non-applicant firms. Enova pursues these objectives by allocating funds from a fixed annual budget to so-called program areas, which define categories of green investments eligible for subsidy.

Each program area issues a call for applications that explains how projects will be assessed under Enova's objectives of direct and indirect emission reductions. In most program areas, projects are assessed solely based on their potential to directly reduce emissions within the applicant firm. In these program areas, subsidy applications are ranked by their expected direct emission reductions per subsidy cost, and subsidies are awarded sequentially until the program's budget is exhausted. Combined with data on the expected and realized direct emission effects for all funded projects, the allocation rule allows us to identify the marginal and inframarginal projects within each program area and their corresponding carbon emission outcomes.

In a subset of program areas, comprising less than 10% of applications in our sample, the projects are assessed and ranked not only based on direct emission effects but also on their potential for indirect emission effects through spillovers to non-applicant firms.[2] Since Enova does not measure or record indirect emission effects, we do not observe such spillovers in the data. However, in the empirical analysis, we allow for the possibility of large unmeasured spillovers.

In Section III, we use our data to describe what it means to win an Enova subsidy. To do so, we implement an event-study specification that compares subsidy winners in a given year to firms that apply and lose in that same year, before and after the application. We consider several firm outcomes, including subsidy payments, capital investment, and output, based on balance sheet and income statement data. The evidence shows that subsidy winners, on average, increase their capital stock by nearly the exact amount promised in their applications to Enova. This suggests that winning a subsidy neither crowds out nor crowds in other investment: It simply induces the firm to undertake a green investment it otherwise would not have made.

In Section IV, 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 carbon emission reductions by allocating a fixed climate budget across Enova's program areas or to an alternative green policy. We incorporate that fund allocation in some program areas is based solely on direct emission effects, while in others it is supposed to reflect both direct and indirect emission effects. We also 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 emissions. For example, certain programs may be systematically favored because they are popular among politicians or expected to benefit certain regions or interest groups.[3] The

[2] Enova's mandate makes clear that (direct or indirect) effects unrelated to carbon emission reductions, such as job creation, should not be used to determine how projects are ranked.

[3] 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-

model further 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 other than 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 in which the decision-maker has no motives other than carbon emission reductions but selects projects based on 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 expected emission reductions that may differ from the realized ones.

In Section V, we explain how we implement the tests and measures of misallocation given the model described in Section IV and the data discussed in Section II. To test for misallocation, it is necessary to observe realized 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 direct emission reductions of each funded project, as well as the realized direct emission reductions. These data are sufficient to identify the marginally

makers with the principal's stated objectives.

accepted projects and their corresponding emission outcomes for the program areas that consider only direct emission effects. As the alternative policy, we consider the purchase and deletion of emission quotas from the EU Emissions Trading System (EU ETS).[4] While this is consistent with the Norwegian Ministry of Finance's (2021) recommendation for evaluating green policies, we also consider alternative measures of the opportunity cost of funds.

While testing for misallocation is straightforward in programs that consider only direct emission effects, it is more challenging to quantify its magnitude. The main data challenge is that it is difficult to credibly measure the counterfactual returns of rejected Enova projects. In Section V.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).[5] Since the former is unobserved but weakly positive, and the latter is directly 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 projects.

Extending the analysis to all program areas, including those that consider both direct and indirect emission effects when allocating funds, introduces an additional challenge: Enova does not measure or record indirect emission effects. In Section V.F, we show how to construct bounds on how large the indirect effects would need to be to rationalize a given level of misallocation. This analysis exploits hand-collected data from each program's call for applications on the weight, if any, that caseworkers are instructed to place on indirect relative to direct emission effects.

In Section VI, we present five sets of main results on misallocation. The first is concerned

[4]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).

[5]See Low and Pistaferri (2025a) for an analysis of Type I and Type II errors in the context of disability insurance.

with *testing* for misallocation in program areas that consider only direct emission effects. We find substantial dispersion in marginal carbon emission reductions across these program areas and strongly reject the null of no misallocation. Furthermore, a large majority of Enova program areas have marginal emission reductions below those achievable in the alternative green policy; we can strongly reject that Enova's marginal emission reductions are equal to those of the alternative policy, suggesting pervasive misallocation at least on the margin.

The next set of results concerns the *measurement* of misallocation in the programs that consider only direct emission effects. 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 programs, the decision-maker could have achieved the current level of emission reductions at less than half the cost. We also report a point estimate that is modestly larger, and an upper bound that is consistent with even greater misallocation.

The third set of results concerns the *sources* of misallocation in the programs that consider only direct emission effects. 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 fourth set of results concerns the *margins* of misallocation in the programs that consider only direct emission effects. 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.

The final set of results extends the analysis to all program areas, including those that consider both direct and unmeasured indirect emission effects when allocating funds. We find that the decision-maker could have achieved the same level of emission reductions with 56% or less of the expenditure even if the indirect emission effects were twice as large as the direct emission effects. Existing evidence suggests that spillover effects of this magnitude are unlikely.[6] Furthermore, we find that misallocation remains non-negligible even if the indirect emission effects are an order of magnitude larger than the direct emission effects.

In Section VII, we offer concluding remarks and discuss the implications of our findings for policymakers and researchers. We argue that 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 in settings other than green investment 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., 2026; see Gillingham and Stock, 2018 for a review).[7] However, as explained by Heckman et al. (1998) and

[6] See Hahn et al. (2026) for a discussion of estimates of the spillover effects of various types of green policies.

[7] A large literature evaluates the effect of specific environmental subsidies, such as for EVs (e.g., Jacobsen et al.,

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-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.

The approach we take to measuring misallocation complements the work of Cingano et al. (2025). While they show how to measure misallocation of public subsidies by extrapolating marginal returns to the returns of inframarginal projects, we show how to construct lower and upper bounds on misallocation under weaker assumptions. In addition, we show how to incorporate unmeasured spillovers and how to isolate the sources of misallocation, allowing us to distinguish between misallocation due to prediction errors and the decision-maker's other motives.

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).[8] We provide evidence that

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.

[8] 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).

green investment subsidies can raise firms' investments in projects that reduce carbon emissions.[9] 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 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. In the course of doing so, we also introduce some notation that will be useful both in the economic model in Section IV and the econometric analysis in Sections V–VI.

A. Institutional context

Context. Norway is a small open economy with a GDP per capita comparable to that of the U.S.[10] Under the Paris Agreement, Norway has promised to reduce its carbon emissions by 55% by 2030 relative to 1990 levels. The country's 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.

[9] 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).

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

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.[11]

Mandate and program areas. Enova's mandate and funding are determined by the Norwegian government through the Ministry of Climate and Environment. As described in its four-year management agreement with the Ministry of Climate and Environment, Enova is given two objectives for allocating funds (Ministry of Climate and Environment and Enova SF, 2020). The first is to *directly* reduce the carbon emissions of applicant firms. This is to be achieved by subsidizing the adoption and use of mature green technologies, such as central heating systems or electric heavy machinery. The subsidized green technology should directly reduce the energy consumption or carbon emissions of the applicant firm.[12] The second objective is to *indirectly* reduce carbon emissions through spillover effects from the green investment in the applicant firm to non-applicant firms. The idea is that these green investments may help support innovation, development, and diffusion of new green technologies that reduce global emissions.

Enova pursues its objectives of direct and indirect carbon emission reductions by allocating funds from a fixed annual budget to so-called program areas, which define categories of green investments eligible for subsidy. In 2022, there were 38 program areas. These program areas are grouped by Enova into eight broad topics: Biogas and biofuel, energy systems and heating, manufacturing, buildings and construction, infrastructure, technology development, land transportation, and maritime transportation. Appendix Table A.I lists the programs in our sample by topic.

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

[12] As explained in Section II.C, our measures of carbon emissions account for reductions in energy consumption by converting energy use into CO_2 equivalents using standard conversion factors.

Each program area issues a call for applications that explains how projects will be assessed under Enova's objectives. In most program areas, the call focuses solely on direct carbon emission effects, which we denote by Δ^D. Applicants must state the green investment they seek to make along with an anticipated direct emission effect. Enova then forms its own expectation of the direct emission effect, which we denote by $\mathcal{E}(\Delta^D)$, and uses this to assess projects.

In other program areas, the call for applications additionally considers indirect carbon emission effects, which we denote by Δ^I. As shown in Appendix Table A.II, the calls for applications in 13 program areas consider indirect emission effects, accounting for less than 10% of applications in our sample. In these program areas, applicants must state an anticipated direct emission effect, but are not asked to substantiate any indirect emission effects due to spillovers to other firms. Enova then forms its expectation about both the direct emission effects ($\mathcal{E}(\Delta^D)$) and indirect emission effects ($\mathcal{E}(\Delta^I)$), and uses these expectations to assess projects.

B. The subsidy process

We next describe the four-step subsidy process of Enova, illustrated in Figure 1.

Step 1: Application. In the first step, firms submit applications to the program area that matches the proposed investment. For example, a firm investing in a geothermal heating pump would send its application to the program "*Heating Plants*," while a firm investing in an electric fishing boat would send it to "*Electrification of Maritime Transport*," a separate program.

In the application, each firm specifies the green investment it seeks to make, and an anticipated direct emission effect from undertaking the investment, which we denote by Δ^A. For example, a firm seeking to invest in a geothermal heating pump may report that the investment will reduce its 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 direct emissions for a counterfactual without the subsidy.

The firm is not asked to specify the anticipated indirect effect, if any, of the green investment on the emissions of other firms. The firm specifies a requested subsidy amount in its application. However, the actual subsidy amount, which we denote by c, is determined by Enova based on 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: Expected direct and indirect effects. Applications are evaluated on a program-by-program basis. For each project, a caseworker forms her own expectation of the direct emission effect from undertaking the stated investment, $\mathcal{E}(\Delta^D)$. To do so, the caseworker must assess the firm's expected investment and emissions both with and without the subsidy.

To assess the likely direct emissions with the subsidy, the caseworker reviews reported information 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 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 emissions by only $\mathcal{E}(\Delta^D) = 75$ tons of CO_2 — either because the firm understates emissions with the investment, overstates emissions without the investment, or both.

For the subset of program areas that also consider indirect emission effects, the caseworker must form an expectation of the indirect effect of the stated green investment on the emissions of other firms, $\mathcal{E}(\Delta^I)$. The caseworker has significant discretion in doing so. She is not required to explain how the estimate is formed, nor to record the estimate or disclose it to the applicant.

Step 3: Allocation. Within each program area, the decision to allocate funds should depend on the total expected emission effect per unit of subsidy cost, c. In most program areas, only direct emission effects are considered. In a subset of programs, the total emission effect includes both direct and indirect emission effects. In these cases, the call for applications specifies the relative weights assigned to direct and indirect emission effects in the allocation of funds.

Figure 1 illustrates the subsidy allocation process for four hypothetical program areas, each receiving three applications. Programs 1, 2, and 3 allocate funds solely based on direct emission effects, while Program 4 also considers indirect emission effects when allocating funds.

Consider first Program 1, which illustrates how funding is allocated to projects within a program that considers only direct emission effects. Here, the highest-ranked applications based on direct effects per unit of subsidy cost, $\frac{\mathcal{E}(\Delta^D)}{c}$, receive a subsidy first; the next-highest receive 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 ($D = 0$).

Next, a comparison between Programs 1, 2, and 3 illustrates that the emission return, $\frac{\mathcal{E}(\Delta^D)}{c}$, of the marginal application at q_r^c may vary across program areas for two reasons. The first, evident from comparing Programs 1 and 2, is that some program areas receive less funding than others. For example, Program 1 may accept only one application (Firm 3) because it has limited funding. The next-ranked application is rejected even though it has a higher $\frac{\mathcal{E}(\Delta^D)}{c}$ than the marginal application in Program 2 (Firm 6), which accepts more applications because it receives more funding. The second reason, evident from comparing Programs 2 and 3, is that program areas with similar acceptance rates may attract applications of different quality. For example, Program 2 attracts higher-quality applicants than Program 3. As a result, the marginal applicant in Program 2 (Firm 6) has a higher return $\frac{\mathcal{E}(\Delta^D)}{c}$ than the marginal applicant in Program 3 (Firm 9).

Lastly, consider Program 4, which illustrates how funding is allocated to projects within a program area that considers both direct and indirect emission effects. In this case, a project may be funded because it is expected to have a direct emission return $\frac{\mathcal{E}(\Delta^D)}{c}$, a high indirect emission return $\frac{\mathcal{E}(\Delta^I)}{c}$, or both. For example, in Figure 1, the Enova caseworker ranks Firm 11 above Firm 10 despite Firm 11 having a lower direct emission return, $\frac{\mathcal{E}(\Delta^D)}{c}$.

Step 4: Subsidy award and verification of direct effects. When a subsidy is awarded, Enova and the firm enter into a contract in which the firm receives the subsidy amount c conditional on making the specified green investment. 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 c only after verifying that the contracted green investment has been made. At this stage, Enova also assesses the realized direct effect of the project, Δ^D, which may differ from both the stated (Δ^A) and expected ($\mathcal{E}(\Delta^D)$) 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 direct emissions by only $\Delta^D = 50$ tons of CO_2. These verifications are carried out by Enova caseworkers or, in some cases, independent third-party experts. Enova does not attempt to measure or verify the indirect emission effect, Δ^I, if any.

C. Data and institutional information

Our paper combines two sources of data:

Enova data. We use a new data set on Enova subsidies covering all project applications submitted between 2012 and 2023. The data set was obtained from Enova as part of an official evaluation project commissioned and funded by the Norwegian Ministry of Finance. Our sample comprises 20,745 subsidy applications from 7,010 unique firms processed during the 2012–2023 period.[13] Each

[13]For our main misallocation measures defined in Section IV, we need data on both expected ($\mathcal{E}(\Delta^D)$) and realized (Δ^D) emission effects. We have therefore excluded a small number of projects with missing $\mathcal{E}(\Delta^D)$, and a larger

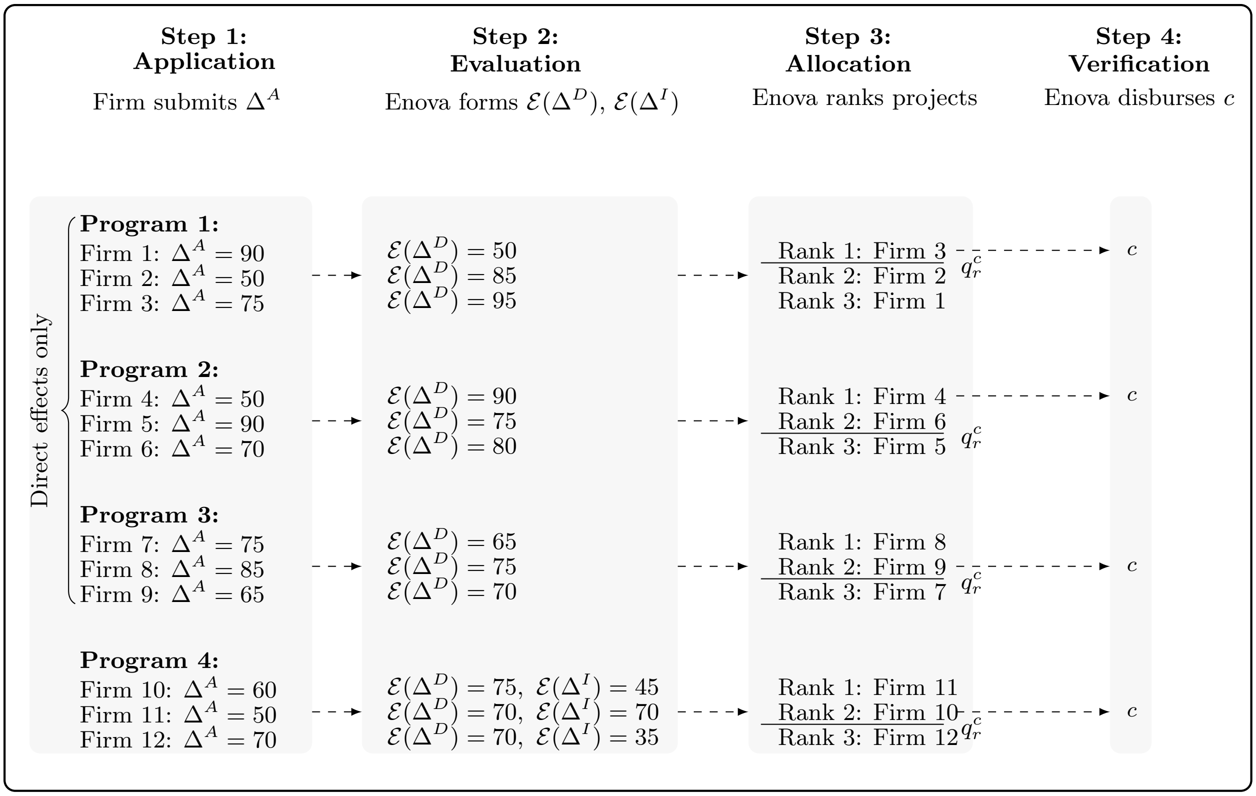


Figure 1. A four-program illustration of the steps in the Enova subsidy process.

application contains complete information on the firm's anticipated direct emission effect Δ^A, and all accepted applications contain complete information on Enova's ex-ante expected direct emission effect, $\mathcal{E}(\Delta^D)$, and the ex-post realized direct emission effect, Δ^D.[14] 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,

number of projects still in process by 2023 (the last year of our sample period) as these lack a recorded Δ^D.

[14] All direct carbon emission effects are reported in present value terms using a 2% annual discount rate. Appendix Table A.IV presents misallocation estimates using alternative discount rates ranging from 0% to 6%. In a few programs, direct emission effects are expressed in terms of energy reductions (kWh) rather than CO_2 reductions. One example is the program "*Energy and Climate Initiatives in Industry*", which reports effects measured in terms of energy reductions. For comparability across programs, we convert energy savings from kWh to CO_2 equivalents using the European energy mix and standard conversion factors from the European Environment Agency.

c. Since Enova does not record its expectation of indirect emission effect, $\mathcal{E}(\Delta^I)$, or measure the realized indirect emission effect, Δ^I, we do not observe these quantities.

We hand-collect historical data from each program area's call for applications on how much weight, if any, caseworkers are instructed to place on indirect relative to direct carbon emission effects. In Appendix II, we present examples of calls for applications to illustrate how we extract the weights from the calls. The data show that caseworkers are instructed to consider possible spillovers in 13 program areas, accounting for less than 10% of our sample of applications; see Appendix Table A.II. In these program areas, the weight assigned to indirect emission effects ranges from 20% to 50% with an average of 23%. In the remaining program areas, project rankings are based solely on direct emission effects, which are observed in the data. In the main empirical analysis in Section VI, we restrict attention to these program areas.

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.

D. 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 97,000, covering 46% of the project's total cost. On average, firms state in their applications that the project will reduce carbon emissions by $\frac{\Delta^A}{c} = 0.18$ tons of CO_2 per subsidy EUR, while Enova expects a reduction of

Table I. Summary Statistics

	Accepted		**Rejected**	
	Mean	*Std.dev*	*Mean*	*Std.dev*
Panel A: Project characteristics				
Subsidy amount in EUR 1000 (c)	97.51	2034	378.3	3100
Stated carbon emission effect (Δ^A/c)	0.18	0.69	0.10	0.37
Expected carbon emission effect ($\mathcal{E}(\Delta^D)/c$)	0.09	0.10	-	-
Realized carbon emission effect (Δ^D/c)	0.08	0.12	-	-
Investment cost share (%)	46.4	1.83	46.0	1.93
Project completion time (months)	6.76	10.04	-	-
Number of projects	13,187		7,558	
	Accepted		**Rejected**	
	Mean	*Std.dev*	*Mean*	*Std.dev*
Panel B: Firm characteristics				
Firm age	19.27	14.55	16.48	13.63
Employees	91.39	287.8	89.56	297.1
Sales	6.39	7.23	5.50	7.01
Wage cost	1.38	1.53	1.23	1.49
Capital cost	0.21	0.27	0.20	0.27
Materials cost	3.19	3.98	2.53	3.68
Number of firms	4,241		3,986	

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 $\mathcal{E}(\Delta^D)$ and Δ^D 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.

$\frac{\mathcal{E}(\Delta^D)}{c} = 0.09$ tons of CO_2 per subsidy EUR.[15]

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 6.4 million in sales, and employs 91 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.

III. Impact of Winning a Subsidy on Firm Outcomes

In Section IV, 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 use our data to describe what it means to win an Enova subsidy.

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:

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

where δ_{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.[16] The inclusion of firm fixed effects

[15] While the average values of $\frac{\mathcal{E}(\Delta^D)}{c}$ and $\frac{\Delta^D}{c}$ are close, at 0.09 and 0.08 tons of CO_2 per subsidy EUR, these averages mask substantial variation across projects. For 77% of projects, Enova either underestimates ($\frac{\mathcal{E}(\Delta^D)}{c} < \frac{\Delta^D}{c}$) or overestimates ($\frac{\mathcal{E}(\Delta^D)}{c} > \frac{\Delta^D}{c}$) the eventual carbon emission effect, with an average gap of 31%, indicating meaningful prediction errors. For the remaining 23% of projects, the expected and realized emission effects coincide.

[16] We estimate δ_{te} for all t and e and then average across t. By doing so, we avoid the problem pointed out by Callaway and Sant'Anna (2021) that cohorts can be negatively weighted in pooled cohort two-way fixed-effect estimators of treatment 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.[17]

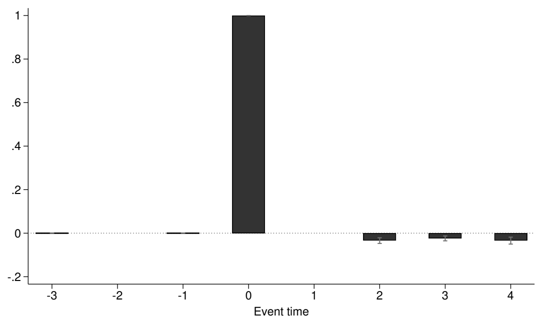
Outcomes from the Enova data. The first set of outcome variables we consider comprises the win probability and value of current and future Enova subsidies. These outcomes, presented in Figure 2, allow us to empirically characterize the treatment associated with winning an Enova subsidy.

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 $e = 0$.

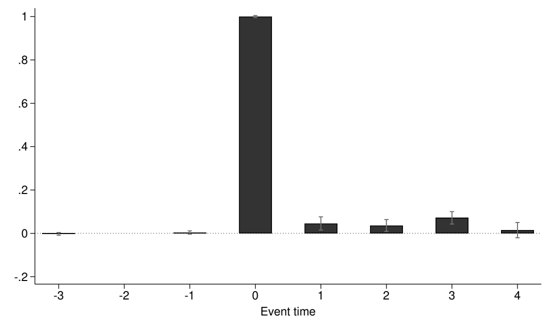
As explained in Section II.A, subsidies are disbursed only after Enova verifies that the contracted green investment has been made. In Panel C of Figure 2, the black line shows mean verified investments among subsidy winners. At $e = 0$, the mean verified investment is around EUR 160,000; by $e = 4$, 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 $e = 4$.[18] Since Enova covers no more than 50% of the

[17] 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.

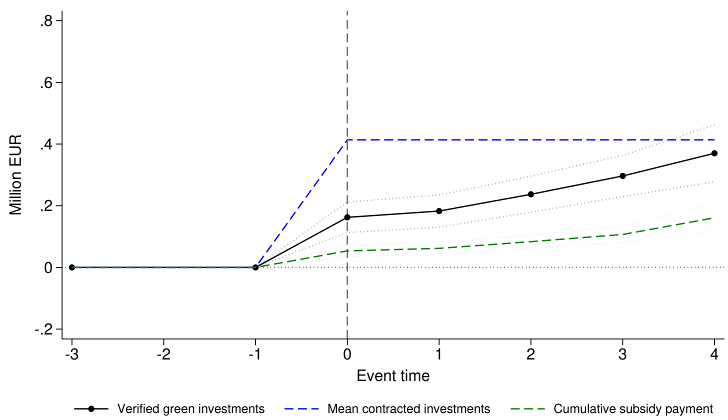
[18] In Appendix Figure A.4, we plot the share of projects that are completed over event time. By event time $e = 2$, 94% of projects are completed; by $e = 5$, the share increases to 98%.



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.

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.

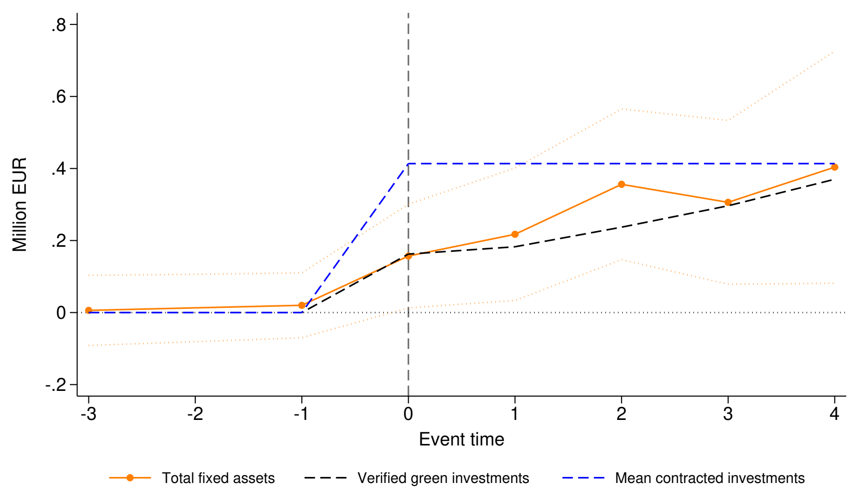


Figure 3. Average investment response. The figure presents estimates from equation (1) of the impact of winning an Enova subsidy. The omitted event time is $e = -2$. The outcome is the firm's fixed tangible assets. Estimated effects are shown in orange, with shaded areas representing 95% confidence intervals. 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.

We measure the firms' cumulative investments as the change in total fixed tangible assets relative to the omitted event time $e = -2$, using the balance sheet data described in Section II.C. 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 the 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 there 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 would have no or little impact on carbon emissions. 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.B.

IV. Measuring Misallocation

We now present a model in which a single 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, 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 total carbon emission reduction if the project is accepted, and let $Y_0(p)$ denote the potential emission reduction if the project is rejected. Observed project-level emission reductions, $Y(p)$, are related to potential emission reductions through $Y(p) = Y_0(p) + D(Y_1(p) - Y_0(p))$. The causal effect on carbon emissions 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. For simplicity, we normalize the mass of applications within each program area to one, and 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:

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

which aggregates total carbon emission reductions across all program areas, including those that are supposed to consider only direct emission effects and those that are supposed to consider both direct and indirect emission effects. To capture this distinction across program areas, it is useful to express a project's total emission effect as

$$\Delta \equiv \frac{1}{\omega_r}\left(\omega_r \Delta^D + (1-\omega_r)\Delta^I\right), \tag{3}$$

where ω_r and $1 - \omega_r$ are the weights placed by the decision-maker on direct (Δ^D) and indirect (Δ^I) emission effects, respectively. As described in Section II.C, $\omega_r = 1$ for the majority of our sample; however, for a subset of programs, it is smaller than one. In these program areas, ω_r may vary for several reasons, including uncertainty about the indirect emission effects of different green technologies and differences in the time horizon over which such effects may materialize.

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:

$$\max_{B_0,\{B_r\}_{r=1}^{R}} \quad \underbrace{\sum_r \overbrace{\int_{q_r^c}^{1} \mathcal{E}[\Delta|r,q_r]\,dq_r}^{\text{Emission reductions}} \quad + \quad \overbrace{\beta_r B_r}^{\text{Other motives}}}_{\text{Enova}} \quad + \quad \underbrace{\Delta_0 B_0}_{\text{Alternative policy}} \quad , \tag{4}$$

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.[19]

Given the decision problem in equation (4), 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:

$$D = \mathbb{I}\Big\{ \frac{\mathcal{E}[\Delta|r,q_r]}{c(r,q_r)} \geq \Delta_0 \; - \beta_r \Big\}. \tag{5}$$

[19] 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 (5) 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:

$$\lambda(r, q_r) \equiv \frac{\Delta(r, q_r)}{c(r, q_r)} - \frac{\mathcal{E}[\Delta|r, q_r]}{c(r, q_r)}. \tag{6}$$

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

$$D = \mathbb{I}\left\{ \frac{\Delta(r, q_r)}{c(r, q_r)} \geq \Delta_0 \ - \beta_r + \lambda(r, q_r) \right\}. \tag{7}$$

Equation (7) 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 (5), we can express the total realized return achieved under the decision-maker's allocation as:

$$\frac{1}{\bar{B}}\Bigg(\underbrace{\sum_r \int_{q_r^c}^1 \Delta(r, q_r) dq_r}_{\text{Return on Enova projects}} + \underbrace{B_0 \, \Delta_0}_{\text{Return on alternative policy}} \Bigg), \tag{8}$$

where B_0 denotes the budget allocated to the alternative policy when the decision-maker selects projects according to the selection rule in equation (5).

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:

$$\tilde{D} = \mathbb{I}\Big\{ \frac{\Delta(r, f_r)}{c(r, f_r)} \geq \Delta_0 \Big\}. \tag{9}$$

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 (7) and (9) imply there is misallocation whenever the marginal returns on Enova's program areas differ from the marginal return in the first-best allocation:

$$\frac{\Delta(r, q_r^c)}{c(r, q_r^c)} \neq \frac{\Delta(r, f_r^c)}{c(r, f_r^c)} = \Delta_0. \tag{10}$$

To see why the inequality above implies misallocation, note that if marginal returns are not equalized 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 (7) and (9):

$$M \equiv \frac{1}{\bar{B}}\underbrace{\left(\sum_r \int_{f_r^c}^1 \Delta(r, f_r)\, df_r + B_0^f \Delta_0\right)}_{\text{First best allocation}} - \frac{1}{\bar{B}}\underbrace{\left(\sum_r \int_{q_r^c}^1 \Delta(r, q_r)\, dq_r + B_0 \Delta_0\right)}_{\text{Actual allocation}}, \tag{11}$$

where B_0^f denotes the budget that is allocated to the alternative policy when the decision-maker selects projects according to the first-best selection rule in equation (9). The first two terms in equation (11) 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 (11) 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:

$$D^{SB} = \mathbb{I}\Big\{ \frac{\mathcal{E}[\Delta|r, q_r]}{c(r, q_r)} \geq \Delta_0 \Big\}, \tag{12}$$

which implies that the ex-ante expected marginal returns are equalized across all program areas within Enova and are 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 (12) is given by:

$$\frac{1}{\bar{B}}\Bigg(\underbrace{\sum_r \int_{q_r^s}^1 \Delta(r, q_r)\, dq_r}_{\text{Return on Enova projects}} \quad + \quad \underbrace{B_0^s\ \Delta_0}_{\text{Return on alternative policy}} \Bigg). \tag{13}$$

where B_0^s denotes the budget that is allocated to the alternative policy when the decision-maker selects projects according to the second-best selection rule in equation (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 (13) from our measure, M, of misallocation in equation (11):

$$\underbrace{M}_{\text{Misallocation}} = \underbrace{M_\beta}_{\text{Other motives}} + \overbrace{\underbrace{M_r}_{\text{Ranking error}} + \underbrace{\Lambda}_{\text{Realization error}}}^{\text{Misallocation from prediction errors}}, \tag{14}$$

where

$$\underbrace{M_\beta}_{\text{Other motives}} = \frac{1}{\bar{B}} \underbrace{\left(\sum_r \int_{q_r^s}^1 \mathcal{E}[\Delta|r, q_r]\, dq_r + B_0^s \Delta_0 \right)}_{\text{Second best: Expected return}} - \frac{1}{\bar{B}} \underbrace{\left(\sum_r \int_{q_r^c}^1 \mathcal{E}[\Delta|r, q_r]\, dq_r + B_0 \Delta_0 \right)}_{\text{Actual: Expected return}},$$

and

$$\underbrace{M_r}_{\text{Ranking error}} = \frac{1}{\bar{B}} \underbrace{\left(\sum_r \int_{f_r^c}^1 \Delta(r, f_r)\, df_r + B_0^f \Delta_0 \right)}_{\text{First best: Realized return}} - \frac{1}{\bar{B}} \underbrace{\left(\sum_r \int_{q_r^s}^1 \Delta(r, q_r)\, dq_r + B_0^s \Delta_0 \right)}_{\text{Second best: Realized return}},$$

and

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

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 (11) 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:

$$\frac{1}{\bar{B}} \sum_r \int_{f_r^A}^1 \Delta(r, f_r)\, df_r. \tag{15}$$

With this definition, we can rewrite our measure of misallocation from equation (11) as:

$$M = \underbrace{\frac{1}{\bar{B}} \sum_r \left(\int_{f_r^c}^1 \Delta(r, f_r)\, df_r + \int_{f_r^A}^{f_r^c} \Delta_0\, c(r, f_r)\, df_r \right)}_{\text{First best allocation}} - \underbrace{\frac{1}{\bar{B}} \left(\sum_r \int_{q_r^c}^1 \Delta(r, q_r)\, dq_r + B_0 \Delta_0 \right)}_{\text{Actual allocation}}. \tag{16}$$

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 (15) from our measure of total misallocation in equation (16), we can decompose M as follows:

$$M = \underbrace{\frac{1}{\bar{B}}\left(\sum_r \int_{f_r^A}^{f_r^c} \left(\Delta_0 - \frac{\Delta(r, f_r)}{c(r, f_r)}\right) c(r, f_r)\, df_r - B_0 \Delta_0\right)}_{\text{Overspending on Enova: } M^O} + \underbrace{\frac{1}{\bar{B}}\left(\sum_r \int_{f_r^A}^{1} \Delta(r, f_r)\, df_r - \sum_r \int_{q_r^c}^{1} \Delta(r, q_r)\, dq_r\right)}_{\text{Misspending within Enova: } M^S}. \tag{17}$$

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. Let q_r^A denote the marginally accepted Enova projects in this second-best autarky allocation. Adding and subtracting the return on the second-best autarky allocation, and using our definition of λ from equation (6), we can then decompose M from equation (11) as follows:

$$M = \underbrace{M_r^O + M_\beta^O + \Lambda^O}_{\text{Overspending on Enova}} + \underbrace{M_r^S + M_\beta^S + \Lambda^S}_{\text{Misspending within Enova}}, \tag{18}$$

where

$$M^O_\beta = \underbrace{\frac{1}{\bar{B}}\left(\sum_r \int_{q_r^A}^{q_r^s} \left(\Delta_0 - \frac{\mathcal{E}[\Delta|r,q_r]}{c(r,q_r)}\right) c(r,q_r)\, dq_r - B_0\Delta_0\right)}_{\text{Overspending due to other motives}},$$

and

$$M^O_r = \frac{1}{\bar{B}}\underbrace{\left(\sum_r \int_{f_r^A}^{f_r^c} \left(\Delta_0 - \frac{\Delta(r,f_r)}{c(r,f_r)}\right) c(r,f_r)\, df_r - \sum_r \int_{q_r^A}^{q_r^s} \left(\Delta_0 - \frac{\Delta(r,q_r)}{c(r,q_r)}\right) c(r,q_r)\, dq_r\right)}_{\text{Overspending due to ranking errors}},$$

and

$$\Lambda^O = \underbrace{-\frac{1}{\bar{B}}\sum_r \int_{q_r^A}^{q_r^s} \lambda(r,q_r)\, c(r,q_r)\, dq_r}_{\text{Realization error for overspending}},$$

and

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

and

$$M^S_r = \frac{1}{\bar{B}}\underbrace{\left(\sum_r \int_{f_r^A}^{1} \Delta(r,f_r)\, df_r - \sum_r \int_{q_r^A}^{1} \Delta(r,q_r)\, dq_r\right)}_{\text{Misspending due to ranking errors}},$$

and

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

V. Implementing the Tests and Measures of Misallocation

We now explain how we implement the tests and measures of misallocation introduced in Section IV. We first restrict attention to program areas that consider only direct emission effects when allocating funds. For these programs, we directly observe the total expected and realized emission effects, $\mathcal{E}(\Delta)$ and Δ. We next extend the analysis to program areas in which total emission effects capture both direct (Δ^D) and indirect (Δ^I) emission effects. As explained below, this introduces an additional identification challenge because indirect emission effects are not observed.

A. Testing for misallocation

To test for misallocation, it follows from equation (10) 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.C, 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.[20] In robustness analyses in Section VI.F, we present results based

[20] As explained in Section IV.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

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 (11) 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):

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):*

$$M = \frac{1}{\bar{B}}\left(\sum_r \int_0^1 \underbrace{\mathbb{I}[\tilde{D} > D]\left(\frac{\Delta(r, f_r)}{c(r, f_r)} - \Delta_0\right) c(r, f_r)}_{\text{Type I: Wrongly rejected projects}} + \underbrace{\mathbb{I}[\tilde{D} < D]\left(\Delta_0 - \frac{\Delta(r, f_r)}{c(r, f_r)}\right) c(r, f_r)}_{\text{Type II: Wrongly accepted projects}} \, df_r\right). \tag{19}$$

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.

setting since the EU ETS market for emission quotas is large relative to Norway's spending.

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:*

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

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

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:*

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

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 all 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.[21]

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.*

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

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:*

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

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

[21] 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.

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 (14) 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).*

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

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:*

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

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

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, are given by:*

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

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

Proof: See Appendix Section I.F.

It follows directly from Proposition 2b and the decomposition in equation (14) 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 $M_r \geq 0$. 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 (11), (14), and (17) that we can point-identify M, its sources, and margins.

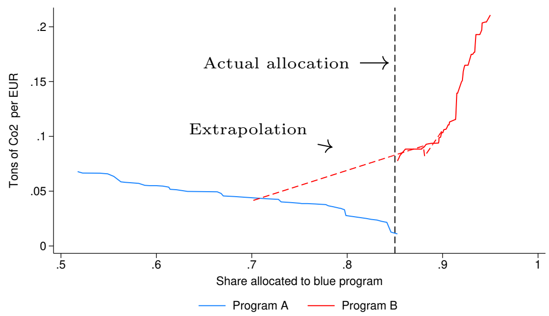
Figure 4 illustrates the extrapolation approach for two major program areas. Panel A shows that marginal realized returns are not equalized across these programs, allowing us to directly reject the hypothesis of no misallocation. Specifically, the decision-maker could achieve higher returns for the same level of spending by reallocating funds from Program A to Program B. This reallocation would shift the vertical 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 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 Appendix Figure A.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.

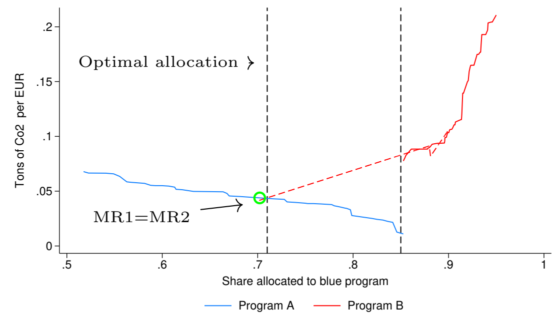
Another step we take to address concerns about the extrapolation approach is to report estimates using a wide range of estimation bandwidths, as illustrated in Panel C of Figure 4. Since reducing the estimation bandwidth limits the extent of reallocation the decision-maker can implement relative to the (unrestricted) decision-maker considered in Section IV, 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.

F. Bounding misallocation with indirect emission effects

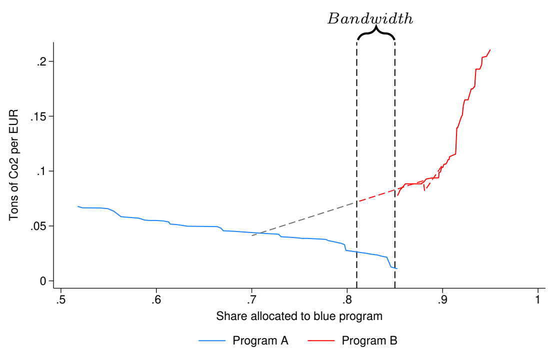
We now broaden the analysis to all program areas, including those that consider both direct (Δ^D) and indirect (Δ^I) emission effects when allocating funds. Using the link between total, direct, and



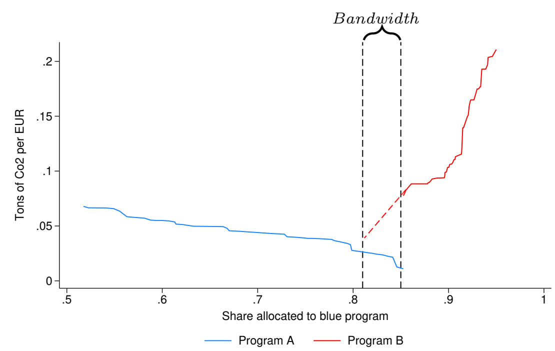
A) Actual allocation



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 and Program B. Panel A shows realized 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%.

indirect emission effects in equation (3), we can re-express our lower bound on M from Proposition 1a in terms of the set of programs $\mathcal{R}^D \equiv \{r : \omega_r = 1\}$ that consider only direct emission effects and the set of programs $\mathcal{R}^I \equiv \{r : \omega_r < 1\}$ that also consider indirect emission effects:

$$\begin{aligned} M^{LB} = & \underbrace{\frac{1}{\bar{B}} \sum_{r \in \mathcal{R}^D} \int_0^1 I[\tilde{D} < D] \left(\Delta_0 - \frac{\Delta^D(r, f_r)}{c(r, f_r)} \right) c(r, f_r)\, df_r}_{\text{Lower bound: Programs that consider only direct effects}} \\ & + \underbrace{\frac{1}{\bar{B}} \sum_{r \in \mathcal{R}^I} \int_0^1 I[\tilde{D} < D] \left(\Delta_0 - \frac{\Delta^D(r, f_r) + \frac{(1-\omega_r)}{\omega_r} \Delta^I(r, f_r)}{c(r, f_r)} \right) c(r, f_r)\, df_r}_{\text{Lower bound: Programs that consider both direct and indirect effects}} . \end{aligned} \tag{20}$$

To compute M^{LB} in equation (20), it is useful to define τ as a parameter governing how large unmeasured indirect emission effects are relative to direct emission effects: $\Delta^I(r, f_r) = \tau \Delta^D(r, f_r)$. In the empirical analysis, we compute M^{LB} over a range of values of τ, showing sensitivity of the measurement of misallocation to the magnitude of unmeasured spillover effects.

VI. Tests and Measures of Misallocation

We now present our empirical results on misallocation. In Sections VI.A and VI.B, we test for and measure misallocation. Next, in Sections VI.C and VI.D, we decompose misallocation into its sources and margins. In Section VI.E, we extend the analysis to include all program areas, including those that also consider indirect emission effects, followed by several robustness tests in Section VI.F. Lastly, in Section VI.G, we describe the correlates of misallocation.

Throughout this section, we estimate carbon emission returns separately by program area and year. We use these returns to rank projects within each program area and year. Given the annual emission return in the alternative policy, we can then identify the first-best and second-best allocations. Next, we calculate the annual carbon emission returns achieved under the first-best 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 of forgone carbon emission reductions.

A. Testing for misallocation

Recall from equation (10) that we have misallocation whenever marginal realized returns in a given year are not equalized across Enova's program areas and not equal to the return of the alternative policy in that year. We present our tests of misallocation in Figure 5. For each program and year, we compute the difference in realized return between the marginally accepted Enova project and the return of the EU ETS. The percentile distribution of these differences is then plotted in Figure 5. Under the null hypothesis of no misallocation, all these differences would be zero.

We find that a large majority of Enova's program areas have marginal realized returns that fall below the return attainable in the alternative policy in the same year. We strongly reject the null hypothesis that the realized returns on marginally accepted Enova projects are equal to the return of the alternative policy in the same year at any conventional level of statistical significance (with a p-value below 0.001).

There is considerable dispersion in marginal realized returns across Enova's program areas within a given year. The within-year standard deviation in marginal realized returns is 0.026 tons of CO_2 per Euro. We strongly reject the null hypothesis of equalized marginal realized returns across Enova's program areas (with a p-value below 0.001).

B. Measuring total misallocation

As explained in Section V, the loss in realized emission 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 6. To construct this figure, we first calculate the difference in realized emission returns between each

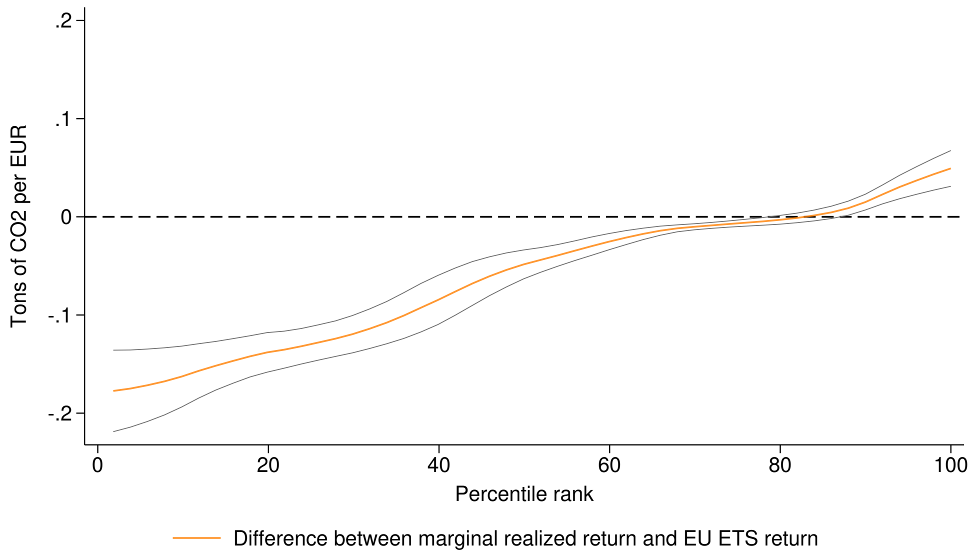


Figure 5. Testing for misallocation. The figure shows the percentile distribution of the differences by program area and year between marginal realized emission returns in Enova and the EU ETS return. Positive values indicate that the marginal realized return for a given program area and year exceeds the return of the EU ETS in the same year. The gray bands indicate 95% confidence intervals based on bootstrapped standard errors.

accepted Enova project and the emission return attainable in the alternative policy in the same year. We then plot the percentile distribution of these return differences in Figure 6.

We find that around 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 6. 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 0.048 tons of CO_2 per Euro, which corresponds to 84% of the (cost-weighted) average return on accepted Enova projects.[22] Scaling this estimate by total spending, we find that this lower bound estimate amounts to 1.052 million tons of forgone emission reductions, or about 2% of Norway's total annual emissions. Put differently, Enova could have achieved the current level of carbon emission reductions with 54% or less of the expenditure.[23]

[22] The cost-weighted average return of accepted Enova projects is 0.057 tons of CO_2 per Euro.

[23] 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

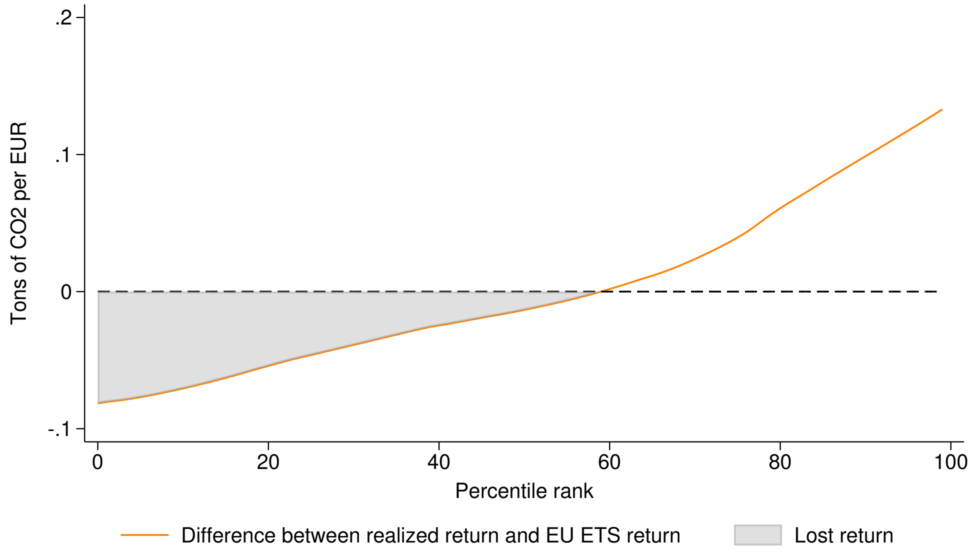


Figure 6. Bounding misallocation. The figure shows the percentile distribution of the differences between the realized emission returns on accepted Enova projects and the EU ETS return in the same year. Positive values indicate that the realized return for a given Enova project exceeds the return of the EU ETS in the same year. The gray shaded area represents the loss in return from funding Enova projects with returns below the EU ETS.

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 158% of the average return on accepted projects — for the same level of spending by optimally reallocating funds.

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 (11). Our point estimate is presented in column (2) of Panel A, Table III. We find that Enova could have increased its emission return by 0.050 tons of CO_2 per Euro by optimally reallocating funds, corresponding to 88% of the average return on accepted projects. Thus,

(0.057 tons of CO_2 per Euro) plus the lower bound estimate of misallocation (0.048 tons of CO_2 per Euro).

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	0.048	0.050	0.090	1.052	1.096	1.965
Panel B: Misallocation due to other motives						
M_β	0.043	0.045	0.084	0.942	0.986	1.841
Panel C: Misallocation due to prediction errors						
$M_r + \Lambda$	-0.036	0.005	0.047	-0.789	0.110	1.030
M_r	0.000	0.001	∞	0.000	0.022	∞
Λ	-∞	0.004	0.047	-∞	0.088	1.030

Notes: Panel A shows our bounds and point estimate of total misallocation, M, as given by Proposition 1b and equation (11), 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 (14). We report misallocation in terms of tons of CO_2 per Euro (*Return*) and million tons of CO_2 (*Emission*).

the point estimate is very close to the lower bound estimate in column (1).

C. *Sources of misallocation*

It follows from equation (14) 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 is almost entirely driven by non-emission motives. Specifically, 90% of total misallocation can be attributed to the decision-maker's non-emission motives, compared to only 10% 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 0.043 and 0.084. By dividing the lower bound on M_β by the upper bound on M, we conclude that at least 48% 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 negative.

D. Margins of misallocation

It follows from equation (17) 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 0.043 tons of CO_2 per Euro, corresponding to about 75% 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 0.007 tons of CO_2 per Euro, corresponding to about 12% of the average return and 14% of total misallocation.

In Panel B of Table IV, we further decompose our point estimate of overspending and misspending into parts related to the decision-maker's non-emission motives and prediction errors, as described in equation (18). We find that non-emission motives are the primary driver of overspending, accounting for about 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.

Table IV. Margins of Misallocation

	Return	**Emission**
Panel A: Margins of misallocation		
M^O	0.043	0.942
M^S	0.007	0.153
Panel B: Decomposing the margins		
M^O_β	0.034	0.745
M^O_r	0.000	0.000
Λ^O	0.009	0.197
M^S_β	0.011	0.241
M^S_r	0.001	0.022
Λ^S	-0.005	-0.110

Notes: The table shows point estimates of the margins of misallocation and their decomposition, as given by equations (17) and (18). We report misallocation in terms of tons of CO_2 per Euro (*Return*) and million tons of CO_2 (*Emission*).

E. *Bounding misallocation with indirect emission effects*

We now broaden the analysis to all program areas, including those that consider both direct and indirect emission effects when allocating funds. As explained in Section V.F, we can construct lower bounds on total misallocation in the full sample of program areas under different assumptions about the magnitude of indirect emission effects. We compute these bounds in Panel A of Appendix Figure A.6 using data on the weights assigned by Enova's caseworkers to direct (ω_r) and indirect ($1 - \omega_r$) emission effects. We consider values of the spillover parameter τ ranging from zero (no indirect effects) to 50 (indirect effects are 50 times larger than direct effects).[24]

Assuming no spillover effects ($\tau = 0$), we obtain a lower bound on total misallocation of 0.050 tons of CO_2 per Euro in the full sample of program areas, which is comparable to the estimate in Table III for the restricted sample. Allowing for indirect effects that are half the size of direct

[24] In a few program areas, Enova caseworkers are instructed to consider both direct and indirect effects, but the weights applied to each are not explicitly stated in the call for applications. In these cases, we assign weights equal to the average weight across other programs that consider both direct and indirect effects.

effects ($\tau = 0.5$), the lower bound declines to 0.048 tons of CO_2 per Euro. When indirect effects are twice as large as direct effects ($\tau = 2$), the lower bound falls to 0.044 tons of CO_2 per Euro. This estimate implies that the decision-maker could have achieved the same level of emission reductions with 56% or less of the expenditure. The estimates in Appendix Figure A.6 indicate non-negligible misallocation even when indirect effects are $\tau = 50$ times larger than direct effects.

A possible concern with the above analysis is that there might be measurement error in ω_r. For example, it could be that some of the program areas that we classify as having an ω_r of one actually consider indirect emission effects when ranking projects. An extreme assumption would be that *all* programs — including those that we classify as having an ω_r of one — have an ω_r equal to 0.77, the average ω_r across programs that consider both direct and indirect emission effects. The corresponding lower bound estimates are reported in Panel B of Appendix Figure A.6. Even under this extreme assumption, we find that misallocation remains non-negligible even if the indirect emission effects are an order of magnitude larger than the direct emission effects.

F. Sensitivity analyses

Extrapolation. As explained in Section V, 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 V, 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.III, 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.III, 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 of 0.020 tons of CO_2 per Euro, corresponding to about 35% of average returns on Enova projects. In the bottom rows of Table A.III, we find that increasing the slope on the extrapolation by a stringent 50% has no material impact on our estimates.

Opportunity cost of funds. In Table III, we bound and estimate total misallocation by comparing the carbon emission returns of Enova projects to the emission returns that could have been achieved by purchasing and deleting emission quotas in the EU ETS. While this is consistent with the Norwegian Ministry of Finance's (2021) recommendation for evaluating green policies, we also consider alternative measures of the opportunity cost of climate funds.

In Figure 7, we plot our lower bound on total misallocation as a function of the chosen opportunity cost, measured in terms of the abatement cost (Euro per ton of CO_2) of the alternative green policy. When the abatement cost is low, the alternative policy delivers a large carbon emission reduction per Euro, and the opportunity cost is therefore high. The figure shows estimates of the lower bound on total misallocation based on abatement costs that are both lower and significantly higher than those implied by the EU ETS, our baseline alternative policy.

Our lower bound on misallocation increases from 0.048 to 0.122 tons of CO_2 per Euro when Enova projects are compared to subsidies for preventing tropical deforestation, which are estimated in the literature to have a low abatement cost. The lower bound remains substantial even when the abatement cost meaningfully exceeds that implied by the EU ETS. For example, our lower bound estimate is 0.016 tons of CO_2 per Euro (28% of the average return on accepted projects) when Enova projects are compared to the carbon tax rate in Norway, which implies an abatement cost that is almost twice as large as that implied by the EU ETS. Decreasing the opportunity cost of funds further mechanically leads to smaller lower bound estimates of misallocation.

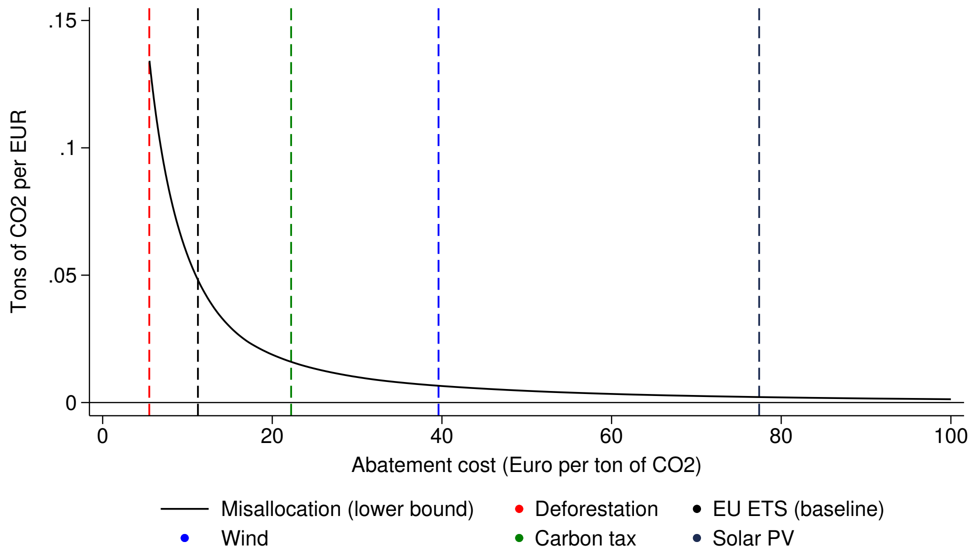


Figure 7. Sensitivity to the opportunity cost of climate funds. The figure shows the lower bound estimate of total misallocation as a function of the opportunity cost of funds, measured in terms of the abatement cost (Euros per ton of CO_2) of alternative green policies. The black dashed line shows the average abatement cost associated with purchasing and deleting emission quotas in the EU ETS over the sample period. The red dashed line shows the abatement cost associated with subsidies to prevent tropical deforestation based on estimates from Harding et al. (2021) and Assunção et al. (2023). The green dashed line shows the average abatement cost implied by the Norwegian carbon tax rate over the sample period. The blue and dark blue dashed lines, respectively, show the abatement costs associated with subsidies for wind and solar power based on estimates from Hahn et al. (2026).

G. *Correlates of misallocation*

As explained in Section II, program areas are grouped by Enova into eight broad topic areas, reflecting the different types of green technologies eligible for subsidy. A natural question is whether funding is systematically skewed toward certain technologies. To answer this question, Figure 8 plots the correlation between each topic and the expected marginal return relative to the alternative policy, $\frac{\mathcal{E}[\Delta|r,q_r^c]}{c(r,q_r^c)} - \Delta_0$. We consider all program areas and 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 topic areas, 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 emission returns across topic areas also explain a substantial share of the variation in marginal emission 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 for programs in two topic areas — land transportation and maritime transportation — both of which are relatively overfunded with low marginal emission returns, as shown in Figure 8.

VII. 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 the decision-maker 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 expected and realized emission reductions for each project. We find that the decision-maker is able ex-ante to identify the projects with the highest ex-post emission reductions, but unwilling to select them.

Our findings are relevant to both policymakers and researchers. The process of allocating subsidies in Enova is organized around specialized programs. Most of these programs are targeted at

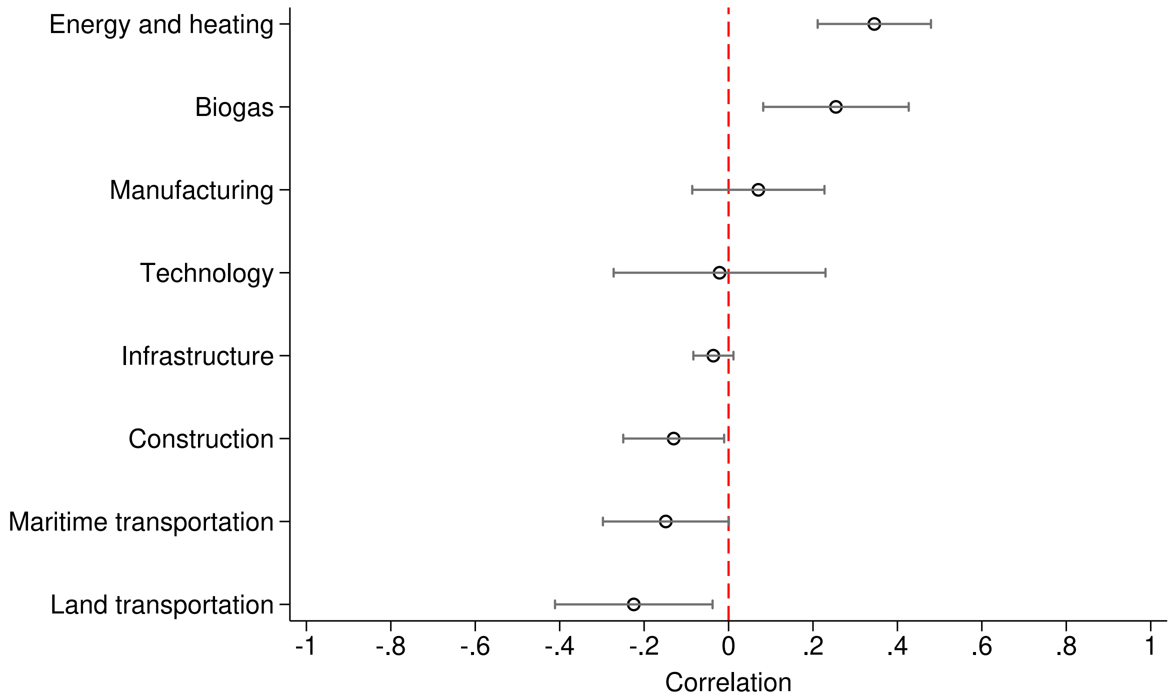


Figure 8. Correlates of misallocation on the margin. The figure shows the correlation between each topic area and the expected marginal return relative to the alternative policy, $\frac{\mathcal{E}[\Delta|r,q_r^c]}{c(r,q_r^c)} - \Delta_0$. For each topic area, the dot reports the correlation coefficient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

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. (2026), which tends to conflate average and marginal outcomes when assessing the efficiency of climate policies.

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Appendix

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 (13) from our measure of misallocation in equation (11):

$$M = \overbrace{\frac{1}{\bar{B}}\underbrace{\left(\sum_r \int_{f_r^c}^1 \Delta(r, f_r)\, df_r + B_0^f \Delta_0\right)}_{\text{First best: Realized return}} - \frac{1}{\bar{B}}\underbrace{\left(\sum_r \int_{q_r^s}^1 \Delta(r, q_r)\, dq_r + B_0^s \Delta_0\right)}_{\text{Second best: Realized return}}}^{\text{Ranking error } M_r}$$
$$+ \frac{1}{\bar{B}}\underbrace{\left(\sum_r \int_{q_r^s}^1 \Delta(r, q_r)\, dq_r + B_0^s \Delta_0\right)}_{\text{Second best: Realized return}} - \frac{1}{\bar{B}}\underbrace{\left(\sum_r \int_{q_r^c}^1 \Delta(r, q_r)\, dq_r + B_0 \Delta_0\right)}_{\text{Actual: Realized return}}.$$

Collecting terms, we have that:

$$M = \underbrace{M_r}_{\text{Ranking error}} + \frac{1}{\bar{B}}\underbrace{\left(\sum_r \int_{q_r^s}^1 \Delta(r, q_r)\, dq_r + B_0^s \Delta_0\right)}_{\text{Second best: Realized return}} - \frac{1}{\bar{B}}\underbrace{\left(\sum_r \int_{q_r^c}^1 \Delta(r, q_r)\, dq_r + B_0 \Delta_0\right)}_{\text{Actual: Realized return}}.$$

Next, we use our definition of λ from equation (6) to express the second-best and actual allocations in terms of the decision-maker's ex-ante expected returns:

$$M = \underbrace{M_r}_{\text{Ranking error}} + \frac{1}{\bar{B}}\underbrace{\left(\sum_r \int_{q_r^s}^1 (\mathcal{E}[\Delta|r, q_r] + \lambda(r, q_r)\, c(r, q_r))\, dq_r + B_0^s \Delta_0\right)}_{\text{Second best: Realized return}}$$
$$- \frac{1}{\bar{B}}\underbrace{\left(\sum_r \int_{q_r^c}^1 (\mathcal{E}[\Delta|r, q_r] + \lambda(r, q_r)\, c(r, q_r))\, dq_r + B_0 \Delta_0\right)}_{\text{Actual: Realized return}}.$$

Rearranging, we have that:

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

$$+ \overbrace{\frac{1}{\bar{B}} \left(\underbrace{\sum_r \int_{q_r^s}^{1} \mathcal{E}[\Delta | r, q_r]\, dq_r + B_0^s \Delta_0}_{\text{Second best: Expected return}} \right) - \frac{1}{\bar{B}} \left(\underbrace{\sum_r \int_{q_r^c}^{1} \mathcal{E}[\Delta | r, q_r]\, dq_r + B_0 \Delta_0}_{\text{Actual: Expected return}} \right)}^{\text{Other motives: } M_\beta}.$$

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:

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

Next, we define a second-best overspending component:

$$\frac{1}{\bar{B}} \sum_r \int_{q_r^A}^{q_r^s} \left(\Delta_0 - \frac{\Delta(r, q_r)}{c(r, q_r)} \right) c(r, q_r)\, dq_r. \tag{A.2}$$

Adding and subtracting equation (A.2) from equation (17), we get:

$$\begin{aligned} M = {} & \underbrace{\frac{1}{\bar{B}} \left(\sum_r \int_{f_r^A}^{f_r^c} \left(\Delta_0 - \frac{\Delta(r, f_r)}{c(r, f_r)} \right) c(r, f_r)\, df_r - \sum_r \int_{q_r^A}^{q_r^s} \left(\Delta_0 - \frac{\Delta(r, q_r)}{c(r, q_r)} \right) c(r, q_r)\, dq_r \right)}_{\text{Overspending due to ranking errors: } M_r^O} \\ & + \underbrace{\frac{1}{\bar{B}} \left(\sum_r \int_{f_r^A}^{1} \Delta(r, f_r)\, df_r - \sum_r \int_{q_r^c}^{1} \Delta(r, q_r)\, dq_r \right)}_{\text{Misspending within Enova: } M^S} \\ & + \frac{1}{\bar{B}} \left(\sum_r \int_{q_r^A}^{q_r^s} \left(\Delta_0 - \frac{\Delta(r, q_r)}{c(r, q_r)} \right) c(r, q_r)\, dq_r - B_0 \Delta_0 \right). \end{aligned} \tag{A.3}$$

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

$$M = M_r^O + \underbrace{\frac{1}{\bar{B}}\left(\sum_r \int_{f_r^A}^1 \Delta(r, f_r) df_r - \sum_r \int_{q_r^A}^1 \Delta(r, q_r) dq_r\right)}_{\text{Misspending due to ranking errors: } M_r^S}$$
$$+ \frac{1}{\bar{B}}\left(\sum_r \int_{q_r^A}^{q_r^s} \left(\Delta_0 - \frac{\Delta(r, q_r)}{c(r, q_r)}\right) c(r, q_r) dq_r + \sum_r \int_{q_r^A}^1 \Delta(r, q_r) dq_r - \sum_r \int_{q_r^c}^1 \Delta(r, q_r) dq_r - B_0 \Delta_0\right)$$
$$= M_r^O + M_r^S + \frac{1}{\bar{B}}\left(\sum_r \int_{q_r^A}^{q_r^s} \left(\Delta_0 - \frac{\Delta(r, q_r)}{c(r, q_r)}\right) c(r, q_r) dq_r + \sum_r \int_{q_r^A}^1 \Delta(r, q_r) dq_r - \sum_r \int_{q_r^c}^1 \Delta(r, q_r) dq_r - B_0 \Delta_0\right).$$

Using our definition of λ from equation (6), we have that:

$$M = M_r^O + M_r^S + \frac{1}{\bar{B}}\left(\sum_r \int_{q_r^A}^{q_r^s} \left(\Delta_0 - \frac{\mathcal{E}[\Delta \mid r, q_r]}{c(r, q_r)} - \lambda(r, q_r)\right) c(r, q_r)\, dq_r\right.$$
$$\left. + \sum_r \int_{q_r^A}^1 (\mathcal{E}[\Delta \mid r, q_r] + \lambda(r, q_r)\, c(r, q_r)) dq_r - \sum_r \int_{q_r^c}^1 (\mathcal{E}[\Delta \mid r, q_r] + \lambda(r, q_r)\, c(r, q_r)) dq_r - B_0 \Delta_0\right).$$

Rearranging and collecting terms, we have that:

$$M = M_r^O + M_r^S + \underbrace{\frac{1}{\bar{B}}\left(\sum_r \int_{q_r^A}^{q_r^s} \left(\Delta_0 - \frac{\mathcal{E}[\Delta \mid r, q_r]}{c(r, q_r)}\right) c(r, q_r)\, dq_r - B_0 \Delta_0\right)}_{\text{Overspending due to other motives: } M_\beta^O}$$
$$+ \underbrace{\frac{1}{\bar{B}}\left(\sum_r \int_{q_r^A}^1 \mathcal{E}[\Delta \mid r, q_r] dq_r - \sum_r \int_{q_r^c}^1 \mathcal{E}[\Delta \mid r, q_r] dq_r\right)}_{\text{Misspending due to other motives: } M_\beta^S} + \underbrace{\left(-\frac{1}{\bar{B}} \sum_r \int_{q_r^A}^{q_r^s} \lambda(r, q_r)\, c(r, q_r)\, dq_r\right)}_{\text{Realization error for overspending: } \Lambda^O}$$
$$+ \underbrace{\frac{1}{\bar{B}}\left(\sum_r \int_{q_r^A}^1 \lambda(r, q_r)\, c(r, q_r)\, dq_r - \sum_r \int_{q_r^c}^1 \lambda(r, q_r)\, c(r, q_r)\, dq_r\right)}_{\text{Realization error for misspending: } \Lambda^S}.$$

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 (11) can be expressed as:

$$M = \frac{1}{\bar{B}}\Bigg(\underbrace{\sum_r \int_{f_r^c}^{1} \Delta(r, f_r)\, df_r + B_0^f \Delta_0}_{\text{First best allocation}}\Bigg) - \frac{1}{\bar{B}}\Bigg(\underbrace{\sum_r \int_{q_r^c}^{1} \Delta(r, q_r)\, dq_r + B_0 \Delta_0}_{\text{Actual allocation}}\Bigg). \tag{A.4}$$

Using the selection equations (7) and (9), we can rewrite equation (A.4) as:

$$\begin{aligned} M =& \frac{1}{\bar{B}}\Bigg(\underbrace{\sum_r \int_0^1 \tilde{D} * \Delta(r, f_r) df_r + B_0^f \Delta_0}_{\text{First-best allocation}}\Bigg) \quad - \quad \frac{1}{\bar{B}}\Bigg(\underbrace{\sum_r \int_0^1 D * \Delta(r, f_r) df_r + B_0 \Delta_0}_{\text{Actual allocation}}\Bigg) && \text{(A.5)} \\ =& \frac{1}{\bar{B}}\Bigg(\sum_r \int_0^1 (\tilde{D} - D) * \Delta(r, f_r)\; df_r + \Delta_0 (B_0^f - B_0)\Bigg). && \text{(A.6)} \end{aligned}$$

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

$$\bar{B} = \underbrace{\sum_r \int_0^1 D\, c(r, f_r)\, df_r + B_0}_{\text{Actual allocation: Spending}} = \underbrace{\sum_r \int_0^1 \tilde{D}\, c(r, f_r)\, df_r + B_0^f}_{\text{First-best: Spending}}. \tag{A.7}$$

Using this equality, it follows that:

$$(B_0^f - B_0) = \sum_r \int_0^1 (D - \tilde{D})\, c(r, f_r)\, df_r.$$

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

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

$\square$

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:

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

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:

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

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

so that:

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

where all terms are observed in the data. $\square$

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:

$$M_\beta = \underbrace{\frac{1}{\bar{B}}\left(\sum_r \int_{q_r^s}^1 \mathcal{E}[\Delta \mid r, q_r]\, dq_r + B_0^s \Delta_0\right)}_{\text{Second-best: Expected returns}} - \underbrace{\frac{1}{\bar{B}}\left(\sum_r \int_{q_r^c}^1 \mathcal{E}[\Delta \mid r, q_r]\, dq_r + B_0 \Delta_0\right)}_{\text{Actual: Expected returns}}. \tag{A.9}$$

Using the selection equations (7) and (12), we can rewrite equation (A.9) as:

$$M_\beta = \underbrace{\frac{1}{\bar{B}}\left(\sum_r \int_0^1 D^{SB}\, \mathcal{E}[\Delta \mid r, q_r]\, dq_r + B_0^s \Delta_0\right)}_{\text{Second-best: Expected returns}} - \underbrace{\frac{1}{\bar{B}}\left(\sum_r \int_0^1 D\, \mathcal{E}[\Delta \mid r, q_r]\, dq_r + B_0 \Delta_0\right)}_{\text{Actual: Expected returns}} \tag{A.10}$$

$$= \frac{1}{\bar{B}}\left(\sum_r \int_0^1 (D^{SB} - D)\, \mathcal{E}[\Delta \mid r, q_r]\, dq_r + \Delta_0 (B_0^s - B_0)\right). \tag{A.11}$$

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

$$\bar{B} = \underbrace{\sum_r \int_0^1 D\, c(r, q_r)\, dq_r + B_0}_{\text{Actual allocation: Spending}} = \underbrace{\sum_r \int_0^1 D^{SB}\, c(r, q_r)\, dq_r + B_0^s}_{\text{Second-best: Spending}}. \tag{A.12}$$

Using this equality, it follows that:

$$(B_0^s - B_0) = \sum_r \int_0^1 (D - D^{SB})\, c(r, q_r)\, dq_r.$$

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

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

$\square$

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:

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

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:

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

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 rejected projects are ex-ante 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:

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

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

Under Assumption 2, it further follows that:

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

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

so that:

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

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 emission reductions with the subsidy and promised investment, and $Y(0)$ represents emission reductions 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:

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

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

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

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

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

$\square$

II. Examples: Project Selection Criteria

Here, we describe the project selection criteria in three example program areas.

Example 1: Direct effects only. The first example is a program that considers only direct emission effects. The program is *Zero-emission Construction Machines.* Appendix Figure A.1 shows a screenshot from the funding call. The program's objective is to reduce emissions through the adoption of zero-emission construction machinery, such as electric tractors. Projects are ranked based on cost-effectiveness. In particular, the call clarifies that applications are "*ranked according to the following criterion: cost-efficiency (NOK per kilo CO_2 equivalent).*" The call further states that "*applications with the lowest support required are ranked higher than applications that require more support per kilo CO_2 reduced*," and only the most cost-effective projects receive funding.

7 Rangeringskriterier

De ulike drivlinjene (batteri og hydrogen) konkurrerer i samme konkurranse. Støtte innvilges til prosjektene med lavest rangeringsscore.

Søknader som tilfredsstiller kvalifikasjonskriteriene rangeres etter følgende kriterium:

- Kostnadseffektivitet (kr/kg CO_2 ekv.)

Med kostnadseffektivitet menes støttekrone pr kg CO_2 redusert, der søknadene med lavest støttebehov rangeres høyere enn søknader med behov for mer støtte per kg CO_2 redusert.

Det er konkurranse om midlene, og bare de mest kostnadseffektive prosjektene vil motta støtte.

Figure A.1. Project ranking for *Zero-emission Construction Machines.*

Example 2: Direct and indirect effects (known weights). The second example is a program that considers both direct and indirect emission effects, with explicitly defined weights. The program is *District Heating.* Appendix Figure A.2 shows a screenshot from the call. The program's objective is to reduce energy consumption through the adoption of district heating. Projects are ranked based on cost-effectiveness and the potential for spillovers from the green investment in the applicant firm to the emissions of non-applicant firms. In particular, the call clarifies that applications are "*ranked according to the following criteria: renewable thermal output per support krone (80%) and degree of innovation in the project (20%).*" The call defines the potential for spillovers as the adoption of green technologies that are new or not currently in use in Norway; the idea is that adoption by the applicant firm may increase adoption by non-applicant firms. As described in Section II.C, we convert energy savings from kWh to CO_2 equivalents using the European energy mix and standard conversion factors from the European Environment Agency.

Rangeringskriterier

Følgende rangeringskriterier med vekting legges til grunn:

- Høyt fornybart effektresultat per støttekrone (80%)
- Innovasjonsgrad i prosjektet (20%)

Med effektresultat menes dimensjonerende termisk varmebehov som skal dekkes opp med fjernvarme. Effektbehovet skal være realistisk, dokumenterbart og angitt med brukstid. Effekt angis per kunde og viser målt, beregnet eller anslått dimensjonerende effektbehov på søknadstidspunktet.

Med innovasjonsgrad i prosjektet menes prosjekter som inneholder innovative løsninger og/eller nye forretningsmodeller som tilfredsstiller følgende kriterier:

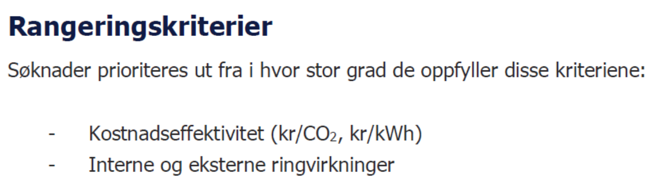
- Teknologien/løsningen er ny eller ikke tatt i bruk i Norge innen det aktuelle segmentet/området
- Søker må dokumentere at innovasjonen har et spredningspotensiale utover det enkelte prosjektet
- Søker må kunne dokumentere at teknologien/løsningen innebærer økt risiko

I søknadsvurderingen vil Enova vurdere prosjektene opp mot hverandre, og rangere ut ifra overnevnte kriterier.

Figure A.2. Project ranking for *District Heating*.

Example 3: Direct and indirect effects (unknown weights). The third example is a program that considers both direct and indirect emission effects, but without explicitly stated weights.

The program is *Energy and Climate Initiatives in Industry*. Appendix Figure A.3 shows a screenshot from the call. The program's objective is to support industrial projects that reduce energy consumption and emissions. Projects are ranked based on cost-effectiveness and the potential for spillovers from the green investment in the applicant firm to the emissions of non-applicant firms. In particular, the call clarifies that applications are "*prioritized based on the extent to which they satisfy the following criteria: cost-effectiveness (NOK per CO_2, NOK per kWh) and internal and external spillovers.*" However, the call does not specify the weight assigned to each criterion.



Rangeringskriterier

Søknader prioriteres ut fra i hvor stor grad de oppfyller disse kriteriene:

- Kostnadseffektivitet (kr/CO_2, kr/kWh)
- Interne og eksterne ringvirkninger

Figure A.3. Project ranking for *Energy and Climate Initiatives in Industry*.

III. Appendix Tables

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

	Means		
Program area	c	$\mathcal{E}(\Delta^D)$	Δ^D
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 baseline sample described in Section II.C. The subsidy amount, c, is expressed in 1000 EUR, while the carbon emission effects ($\mathcal{E}(\Delta^D)$, Δ^D) are expressed in tons of CO_2.

Table A.II. Summary statistics: Program areas that consider both direct and indirect effects

Number of programs that consider indirect emission effects	13
Share of applications in the full sample	7.1%
Maximum weight on indirect emission effects	50%
Minimum weight on indirect emission effects	20%
Average weight on indirect emission effects	23%

Notes: The table summarizes the program areas that consider both direct and indirect emission effects when allocating funds. We restrict attention to the programs represented in our baseline sample described in Section II.C.

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

		Sources			Margins	
	M	M_β	M_r	Λ	M^O	M^S
Baseline	0.050	0.045	0.001	0.004	0.043	0.007
Sensitivity to bandwidth						
Bandwidth = 40	0.020	0.017	0.001	0.002	0.015	0.005
Bandwidth = 60	0.029	0.026	0.001	0.002	0.023	0.006
Bandwidth = 80	0.038	0.034	0.000	0.003	0.032	0.006
Bandwidth = 100	0.050	0.045	0.001	0.004	0.043	0.007
Sensitivity to slope	0.050	0.045	0.002	0.003	0.044	0.006
Sensitivity to bandwidth and slope						
Bandwidth = 40	0.020	0.016	0.002	0.002	0.016	0.004
Bandwidth = 60	0.028	0.025	0.001	0.002	0.024	0.004
Bandwidth = 80	0.037	0.034	0.000	0.003	0.032	0.005
Bandwidth = 100	0.050	0.044	0.002	0.004	0.045	0.005

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 Tables 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.IV. Sensitivity of the lower bounds: Discounting

		Sources		
	M	M_β	M_r	Λ
Baseline	0.048	0.043	0.000	$-\infty$
Sensitivity to changing the discount rate: $r = 0\%$	0.043	0.036	0.000	$-\infty$
Sensitivity to changing the discount rate: $r = 4\%$	0.053	0.048	0.000	$-\infty$
Sensitivity to changing the discount rate: $r = 6\%$	0.056	0.052	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. In the main analysis in Table III, all carbon emission effects are reported in present value terms using a 2% annual discount rate. Rows (2)–(4) examine the sensitivity of the estimates to instead applying a 0%, 4%, and 6% annual discount rate.

IV. Appendix Figures

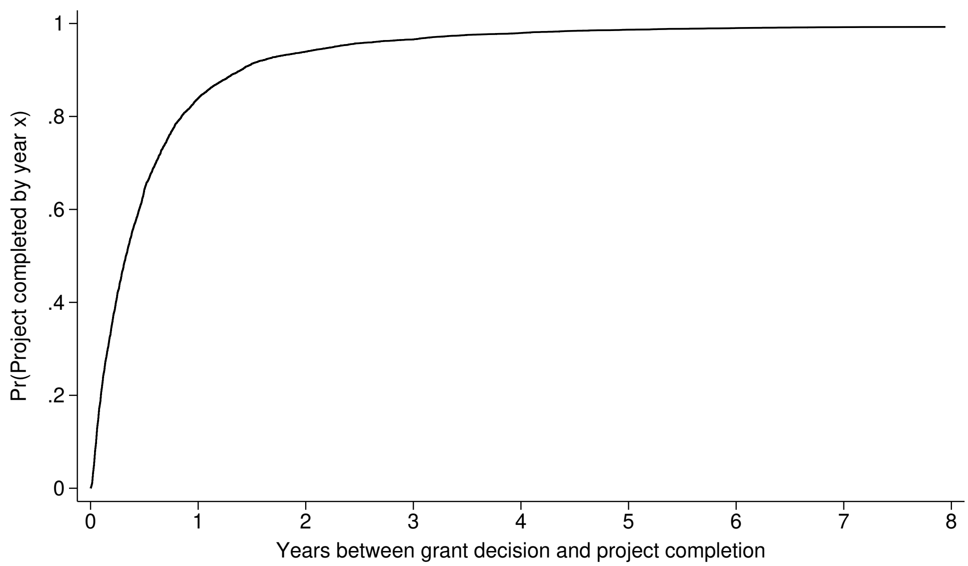


Figure A.4. Project completion. The figure shows the probability that a project is completed within a given number of years relative to the grant decision date. We measure completion using the date the project receives its final payment, as payment is contingent on verification that the investment has been made. The figure is based on a sample of projects accepted before 2020 that can be observed for at least four years.

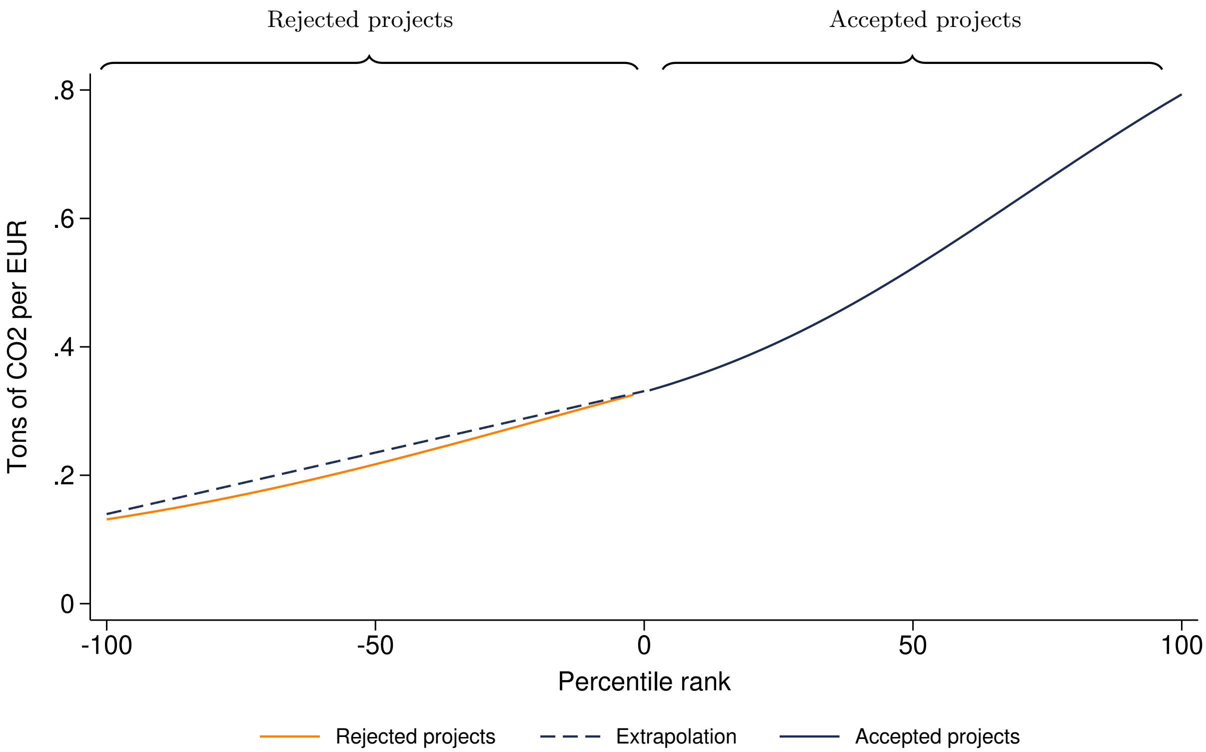
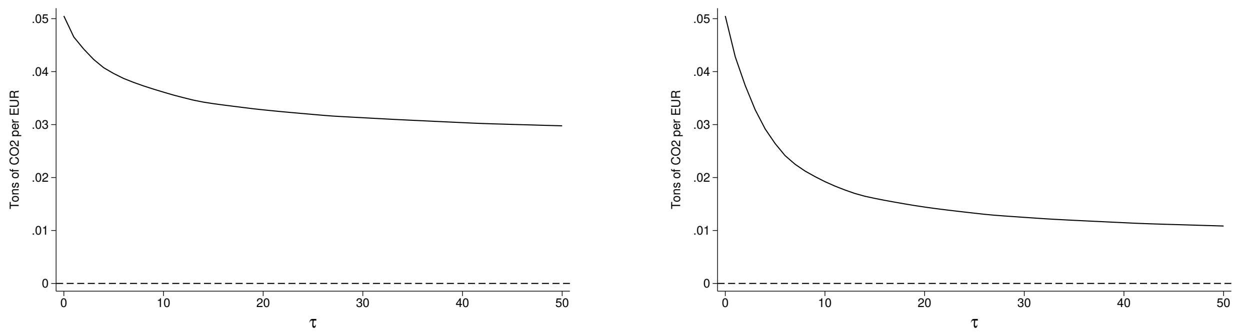


Figure A.5. Illustration: Extrapolating stated returns. The figure applies our extrapolation procedure to stated emission returns reported by firms in their subsidy applications, which are observed for all projects, including rejected ones. The blue line shows the stated return of accepted projects, 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. 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.



Panel A. Using observed weights

Panel B. Using average weights

Figure A.6. Robustness to unmeasured carbon emission effects. In Panel A, we use our data on ω_r to compute M^{LB} from equation (20) for different values of τ on the full set of program areas. In Panel B, we again compute M^{LB} from equation (20) on the full set of program areas, but now assume that $\omega_r = 0.77$ — the average ω_r across programs that consider both direct and indirect emission effects — for all programs.