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Energy State Aid: A Toolbox on Counterfactual Impact Evaluation

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Contents

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1 Introduction

This document aims to provide a Toolbox for the use of Counterfactual Impact Evaluation (CIE) methods in the case of energy State aid interventions. In particular, it seeks to assist Member State (MS) policy officers when devising an evaluation plan to be submitted to the European Commission for adoption and also for writing the Terms of Reference for the tendering of evaluation reports.

State aid interventions take place alongside various economic and social activities. When evaluating the effect of a State aid intervention, one must isolate the policy effect from other effects that may happen at the same time. Otherwise, one may over/underestimate the effect of the intervention. Various econometric methods may be employed to carry this out, which this toolbox outlines.

The Toolbox discusses the intervention logic of the State aid schemes, the distinction between direct and indirect effects and the concept of proportionality and appropriateness of the intervention. Alongside this, the Toolbox presents methods to quantify the impact of energy State aid interventions on CO_2 emissions. The toolbox presents a number of ex-ante simulation and ex-post econometric methods to estimate avoided CO_2 emissions attributable to a State aid intervention. The final section considers the evaluation of auction schemes. The analysis of an auction requires a different approach with respect to other State aid interventions. An auction is designed to procure a service at least cost. Ideally, an evaluation would assess the differences between procurement prices and firm costs. Cost information is private, however. The toolbox provides guidance on two approaches for evaluation to navigate this issue. First, one may consider auction design relative to the structure recommended by theory. There is a greater likelihood of cost-effective deployment if an auction design corresponds closely to that recommended by theory (with suggested guidelines offered). Second, the literature has considered auction performance relative to a benchmark. The toolbox offers guidance when applying such methods.

Good data are a crucial component for effective evaluation. Data collection should be incorporated into the design of the State aid scheme to facilitate the application of the favoured methods. Priority should be given in scheme design to ensure that appropriate data and resources are made available for the preferred evaluation procedure. Where this is impossible and data or resource constraints preclude the use of the favoured methods, second-best methods are presented.

Each subsection focuses on a specific issue, however some overlap between evaluation topics exists. The Toolbox will provide policy officers with practical suggestions that should help when deciding on the methods and data they wish to use in their evaluation. Box 1 provides an overview of the components that an evaluation team may wish to consider.

Box 1: The elements of the evaluation plan

The evaluation plan is a document containing at least the following minimum elements: the objectives of the aid scheme to be evaluated, the evaluation questions, the result indicators, the envisaged methodology to conduct the evaluation, the data collection requirements, the proposed timing of the evaluation including the date of submission of the final evaluation report, the description of the independent body conducting the evaluation or the criteria that will be used for its selection and the modalities for ensuring the publicity of the evaluation.[a]

Especially with reference to the sections concerning evaluation questions and envisaged methodology (sections 3 and 5 of the Annex I - Part III.8 - Supplementary Information Sheet for the notification of an evaluation plan), the evaluation plan should set out clearly the underlying intervention logic of the aid scheme, describing the needs and problems the scheme intends to address, the target beneficiaries and investments, its general and specific objectives, and the expected impact. The main assumptions relating to external factors that might affect the scheme should also be mentioned.

The evaluation plan should also define the scope of the evaluation, i.e. it should include precise questions that can be answered quantitatively and with the necessary supporting evidence. The following is a list of important considerations that are highlighted in this guidance document.

1. Direct impact of the aid on beneficiaries, i.e. the direct effect on the intended parties. For instance, has the aid had a significant and direct effect on a particular outcome or behaviour? (e.g. investment in certain energy technologies; renewable energy deployment).

Procurement auction design should be evaluated, where applicable. A procurement auction is often employed for renewable energy price supports. The appropriate design is often context-specific. An evaluation plan should identify whether the appropriate design has been put in place. A well-performing auction procures a service at a price that is close to the costs of production. Costs of production are private to the firm. Methods to identify whether prices are likely close to expected costs are offered in this Toolbox.

2. Indirect impact of the aid scheme, i.e. the effect of the aid mediated or transmitted through a third party or secondary effects on the intended parties (e.g. distributional impacts of household/firm-level energy supports; impact of intermittent renewable energy deployment on the emissions intensity of residual fossil fuel generation; net employment impacts).

There are indirect effects specific to energy State aid. In particular, one must consider the carbon emissions avoided by the scheme, taking into account potential indirect effects (e.g. impact of increased intermittency in the energy system on the emissions intensity of operating fossil fuel plant).

3. Proportionality and appropriateness of the aid scheme, i.e. whether the aid instrument is adequate to the specific context of the intervention. For instance:

Was there too much/too little support offered? Could the same outcome be achieved with lesser public expenditure?

Was the most effective aid instrument chosen? Would other aid instruments or types of intervention have been more appropriate for achieving the stated objectives (for example, could a loan instead of a grant lead to the same outcome with lesser public expenditure)?

The evaluation should assess, as far as it is possible, the impact of the aid scheme at all three levels, addressing the relevant questions in respect of the scheme's objectives.

The remainder of the Toolbox is organized as follows. Section 2 discusses the intervention logic. Section 3 deals with the identification and measurement of direct effects while Section 4 discusses the evaluation of auction

[a] See for example Art. 2(16) of the GBER or Art. 2.2.(9) of the Regional Aid Guidelines 2021-2027. The European Commission provides a template (Annex I - Part III.8 - Supplementary Information Sheet for the notification of an evaluation plan), which Member States are required to complete to submit an evaluation plan in view of its adoption.

mechanisms. Section 5 discusses the identification and measurement of indirect effects. These discussions are organised in terms of first and second-best evaluation methods, where possible. When evaluating indirect effects, the quantification of carbon emissions attributable to renewable energy State aid is given particular attention. Proportionality and appropriateness of the State aid is discussed in Section 6.

2 The intervention logic

An evaluation must be carried out relative to a stated objective.[b] The Terms of Reference for State aid evaluation should describe the objective of the intervention and the channels through which the intervention will achieve the desired outcome (i.e. the 'intervention logic'). There are two steps when discussing the intervention logic: defining the objective/rationale and grounding the rationale in the appropriate literature.

2.1. Step 1: The direct objective and rationale for intervention must be defined

To effectively evaluate an intervention, the primary objective of the State aid intervention should be first defined. The choice of intervention should be grounded in scientific evidence and/or economic theory. Should State aid intervention be implemented on the grounds of under/over-provision by the market (i.e. a market failure), the intervention should be motivated in this context. Energy State aid interventions often have the objective of correcting a market failure with respect to excessive carbon emissions. Intervention may also be justified on the grounds of de-risking investment. Many novel technologies may be exposed to risks that are difficult to hedge with traditional financial instruments. Similarly, household-level heat incentives may be implemented to overcome behavioural impediments that may persist despite being cost-effective. Alongside these factors, State aid is often motivated on grounds of equity. The benefits and costs associated with a certain outcome may be distributed in an unfair manner across society. Intervention may be appropriate to counter this.

Understanding the rationale is important for understanding the scale and proportionality of the intervention. An evaluation should therefore include a clear description of the objective and how the aid will remedy the identified problem. An objective that is not clearly specified can make evaluation difficult. For instance, a tax exemption for pure and high-blended liquid biofuels may present market penetration as the objective. This is a poor specification. The objective of biofuels deployment is often to reduce CO_2 emissions. Market penetration is the mean of achieving decarbonisation, rather than the ultimate environmental outcome. An appropriate rationale would be to reduce emissions by a certain benchmark. This objective specification then guides evaluation. Assuming that every reduction in tax liability leads to additional biofuel consumption, one may assess whether a given tax exemption is proportionate to the emissions reduction objective.

2.2. Step 2: Evaluation of the intervention logic should be grounded in an appropriate literature review

The objective and rationale for intervention should be supported by a short but effective review of the relevant literature. The academic literature will provide both theoretical and empirical insights into the best intervention to achieve the stated objective, while the grey literature will tend to outline the potential practical impediments affecting implementation. Box 2 mentions a few important elements that should be considered when writing a literature review.

While the academic literature can seem vast, there are a few key points that should be considered. First, one should check that the existing evidence supports the considered scheme design. If a contradiction exists between what is recommended in the literature and the intervention being studied, this must be explained. For instance, there may be contextual reasons why an identified contradiction does not hold. Alternatively, measures introduced to remedy any identified problems may be discussed. These may also be sourced from the literature. Second, one should follow guidance from existing evaluations, which may be instructive when it comes to identifying best practice. There may be good reason to depart from perceived best practice and any departure should be explained. Further details are offered in Box 2.

[b] Indeed, the Common methodology for State aid evaluation 1 states that one must describe 'the needs and problems the scheme intends to address, the target beneficiaries and investments, its general and specific objectives, and the expected impact.'

Box 2: Practical steps when carrying out an effective review of the literature

The review of the literature should be reported in section 1.(4) of the Annex I - Part III.8 - Supplementary Information Sheet for the notification of an evaluation plan.

1. Definition of the objective: this should identify the market failure or the political, social or practical rationale for intervention.

2. A review of academic literature: an internet search should identify some initial academic, policy and evaluation documents relevant to the intervention objective. Having identified a number of starting points, it is suggested to scrutinize citations backwards (documents cited by the article) and forwards (documents that cite the article) and select the most pertinent or influential.

3. One may group the identified studies by topic or 'strand' and summarise the general message emerging from each. Patterns may be useful in guiding this process. For instance, groups of articles or reports with similar intervention instruments, methodologies, findings, etc. can form a strand. Each strand provides useful insight on a particular aspect of appropriate intervention. Meta-analyses and existing literature reviews are often particularly helpful.

4. From this literature review, one may then identify the strengths and weaknesses of a given intervention. For instance, the literature may, generally, advocate an auction system to allocate renewable energy price supports. However, certain studies may have identified contexts where a certain specification is inappropriate. This context should be reviewed when discussing the rationale for a given intervention.

5. When evaluating the literature, one should be cognisant of any apparent shortcomings of a given study and the results interpreted in this context.

6. Comparison with the case at hand: it should be foreseen that the results of the evaluation report are compared to those found in the literature.

2.3. Intervention timeline

This toolbox has provided a number of guidelines when designing the evaluation of State aid. In particular, data availability is an important aspect of evaluation success, with data requirements influenced by the methodology to be applied. It is important that data and methodological aspects are considered at an early stage in the implementation of State aid support to maximise the probability of a successful counterfactual impact evaluation. Table 1 below shows the interventions considered in this document and what considerations are required both pre- and post-implementation.

Table 1: Intervention consideration by implementation stage

	Implementation stage
Randomised Control Trial & Quasi-experimental techniques	The design of RCT or quasi-experimental analyses should ideally be considered pre-implementation, however, there may be opportunities post-implementation, subject to data availability. Considerations pre-implementation could potentially allow for data collection to be incorporated in policy design/implementation.
Procurement auction	The format of auction design should be considered pre-implementation and may also be evaluated post-implementation. Benchmark evaluation; market concentration analysis; and tender data analysis can all be carried out with data received post-implementation.
Indirect effects	The analyses pertaining to input market analysis; portfolio effects; distributional effects; behavioural rebounds; employment effects; subsidising otherwise underperforming firms and carbon leakage are best carried out post-implementation, using data available from the intervention (data collection should be considered pre-implementation). If the results were desired pre-implementation, one could possibly source data from similar interventions or contexts, while simulation studies may also be carried out pre-implementation.
Emissions change	Ex-ante simulation can be carried out pre- and post-implementation. Ex-post estimation can be carried out post-implementation, however, if the results were desired pre-implementation, one could estimate the marginal effects associated with a previous change in renewables capacity, if appropriate to assume that the marginal effects are constant.
Proportionality	Investment viability-based proportionality analyses (e.g. IRR; LCOE-based analyses) may be carried out both pre and post implementation, should cost data be available.

Checklist:

- Identify the primary objective of the intervention
- Identify the rationale for the chosen intervention
- Include a review of the literature in the evaluation report to ensure that the chosen intervention is appropriate. Theory and evidence from the academic literature should support the intervention choice, while grey literature outlining the same or similar aid schemes should be discussed to identify how the intervention should be implemented in practice.

3 Direct effects

As outlined in the guidance document "Common methodology for State aid evaluation", the effects of an intervention can be distinguished as being either direct or indirect [1]. The expected effects must first be identified and defined in the evaluation plan. Common direct and indirect effects pertaining to energy policy are outlined below to aid this identification procedure.

3.1. Defining direct effects

The direct effect is the impact that the intervention has relative to the primary direct objective. This objective is often stated clearly in the decision document. For instance, energy-related State aid is often used to achieve objectives of either environmental sustainability, energy security or market competitiveness and the aid is intended to incentivise an investment or consumption behavior that the beneficiary would normally not pursue in the absence of the aid.

The direct effect relates to whether the aid has effectively contributed to a higher level of investment or consumption compared to what one would expect to happen without the aid. If the firms would have carried out the activity anyway, or with a lesser degree of state aid, then the aid was ineffective in efficiently achieving the desired outcome. The outcome could have happened with lesser or no intervention.

There are many potential direct effects. If the policy objective is to reduce greenhouse gas emissions, then the direct effect is the quantity of avoided emissions attributable to the policy intervention. If the policy objective is to incentivise a switch towards low-carbon electricity generation sources, the direct effect is quantified as the quantity of policy-attributable renewable generated electricity produced in a given period compared to a properly selected counterfactual.

Among the considered evaluation reports, the primary objective tended to revolve around increasing the share of renewable energy. For instance, the UK Renewable Heat Incentive had the objective of increasing the share of heat generated by renewable sources.[2]

Checklist:

- Direct effects relate to the primary objective of the policy, i.e. the additional investment/consumption that the aid is supposed to incentivise.
- Ideally, all identifiable direct effects that are likely to impact the measurement of the direct effect should be accounted for. The listed effects in this section comprise the most common and should be among those considered.

3.2. Quantifying Direct Effects

The quantification of direct effects regards the "additionality" of the policy intervention. Effective quantification of both additionality and proportionality requires adequate data and data collection should be incorporated into the policy design stage. This will maximise the ease and likelihood of an effective impact evaluation.

"Additionality" refers to the additional effect, net of the effect that would have happened absent the policy intervention. The approach to quantify "additionality" depends on the relevant counterfactual. If the counterfactual is clearly zero, such as for renewable energy investments where deployment without policy support is not cost-effective, all capital investments receiving State aid support are "additional". Identifying whether the counterfactual is zero is discussed in detail when discussing proportionality.

This is particularly relevant for household-level installations where non-financial attributes may affect investment. For example, electric vehicles may not be cost-competitive with fossil fuel vehicles; however, households may wish to purchase an electric vehicle at extra cost for comfort. Similarly, state aid may be justified to overcome behavioural barriers limiting an otherwise cost-effective investment. Investments such as those to aid energy efficiency, electric vehicles or renewable heat are most likely to fall under this category.

The first-best approach to calculate policy "additionality" and proportionality when there is a non-zero deployment counterfactual is to use experimental or quasi-experimental methods. These are statistical methods that often require specific types of data. These methods are the gold standard with regard to counterfactual impact evaluation and should be pursued where possible. Potential data sources and applicable methods should be considered early, at the policy design stage if possible. The data requirements vary according to the methodology, and the suitable methodology varies with context. At the design stage, the analyst should consider what methods may be appropriate and incorporate data collection into the procurement design. Each method will be discussed in the following sections, with the data requirements and potential sources outlined.

Gillingham, et al. [3] provide a review of methods. A Randomized Control Trial (RCT) is the gold standard when it comes to identifying the causal effect of a policy intervention, however randomisation is not always possible. Quasi-experimental methods may overcome this constraint, exploiting the available randomisation. Instrumental variables, regression discontinuity, difference-in-differences, fixed-effects and matching methods are all approaches in this space and methodologies suggested by the European Commission [1] in the common methodology for State aid evaluation. Data requirements and the context for application varies by approach and these are discussed in the following subsections.

3.2.1. First-best approach A: Randomised Control Trial (RCT)

A Randomised Control Trial is a form of scientific experiment used to control factors not under direct experimental control. By randomly allocating participants to the treatment group, an RCT enables statistical control over these influences. Provided it is designed well, conducted properly, and enrols enough participants, an RCT can isolate the causal effect of a treatment (e.g. state aid support) on an outcome (e.g. renewable heating installations).

Fowlie, et al. [4] give a good example of how to effectively implement an RCT. While this is not generally possible in the context to randomly assign individuals or firm as recipients of State aid (i.e. the treatment group), there are clever ways to work around this. While receipt of the state aid is not random, receipt/exposure to other 'treatments' may be random. Fowlie, et al. [4], for instance, consider the random exposure to an encouragement scheme which included application assistance. Using an instrumental variables (IV) approach (see following section for further details on IV), the randomized assignment into the encouragement scheme was exploited to identify the causal effect of the policy intervention. This retains the property of treating all policy recipients equally, introducing benign randomisation associated with an encouragement scheme to identify the effect of the State aid intervention.[c] Similar randomisation may be introduced via an advertising or information campaign. This is a clear example where the data collection procedure should be considered at the policy design stage, such that the appropriate mechanism (such as a randomised information campaign) can be put in place.

While the preferred evaluation option, RCTs are resource intensive. Implementation often requires a bespoke experimental program, where participants are randomly allocated to treatment and control groups and a sufficiently large dataset collected. This is difficult to implement relative to a State aid scheme. However, this does not preclude the use of an RCT completely. The methods of Fowlie, et al. [4] demonstrate how related programs, such as an encouragement campaign, may be exploited if assignment into such associated programs is random. Evaluators may wish to explore whether randomized exposure to such a project is possible. However, implementing an instrumental variables approach is required for this to be effective and this may be difficult in practice, as the following subsection will discuss.

[c] All households were freely able to participate in the program or not, with the allocation of the encouragement programme randomized. The experimental sample comprised 34,161 households that were both presumptively eligible for assistance. Approximately one quarter of the sample households were randomly assigned to encouragement treatment. For the remaining households assigned to the control group, consumption and program participation decisions were observed. The causal effect of investment was estimated by using the random assignment to encouragement as an instrumental variable for participation status. In the first stage regression, participation is regressed on encouragement and a set of controls. The second stage substitutes this instrument for adoption in a regression of monthly energy consumption on adoption and a set of controls.

When an RCT cannot be performed due to data or resource constraints, quasi-experimental methods attempt to isolate sources of variation in the data that can be considered plausibly random.[5] Their application is discussed in the next subsection.

3.2.2. First-best approach B: quasi-experimental techniques

Quasi-experimental techniques can also estimate the causal effect of an intervention and should be the first set of techniques considered if an RCT has been ruled out. Each technique is suited to a specific set of circumstances and data requirements. The analyst should consider which technique best suits the evaluation context. Guidelines pertaining to each evaluation technique are outlined below.

Instrumental variables

An Instrumental variable (IV) approach may be used when one cannot exclude factors not under direct experimental control. This technique involves the use of a third 'instrumental variable' which is used to isolate the effect of a treatment on an outcome of interest.

An IV is useful when it is not clear to what extent an explanatory variable (e.g. a price support for home insulation) has influenced an outcome of interest (e..g household energy consumption). It may be the case that there is 'endogeneity' – that there are unobserved factors influencing both the propensity to seek the price support and energy consumption. For instance, more energy-conscious households may seek to upgrade their home insulation and seek a price support, biasing results. To overcome this problem, an instrumental variable is a third variable that isolates the causal effect of the explanatory variable on the outcome of interest.

To effectively apply an instrumental variable (IV) approach, one must find a valid instrument. A valid instrument is correlated with the explanatory variable but has no independent effect on the outcome variable, except through its effect on the explanatory variable (this is the so-called "exclusion restriction"). For instance, exposure to a marketing strategy affects the decision to purchase a new energy efficient appliance, but it should not affect your energy consumption. This allows one to effectively control for the effect of any unobserved factor that may affect both one's decision to select into the purchase of an energy efficient appliance and the energy consumption decision. In this way, one may isolate the causal effect of the explanatory variable on the outcome variable of interest.

A good instrument must have strong explanatory power. That is, it must be strongly correlated with the explanatory variable of interest. Second, it must pass the above-mentioned exclusion restriction and show zero correlation with the outcome variable. This is difficult as it may be the case that the instrument may affect the outcome as well as the explanatory variable. Finally, a good instrument must be uncorrelated with the non-observable factors in the model (i.e. the error term). Finding valid instrumental variables that meet these criteria is often difficult.

Matching

Propensity score matching (PSM) has been developed by Rosenbaum and Rubin [6], with Li [7] providing a practical guide as to how scholars may apply matching procedures in practice. Matching consists of pairing treated firms/households to one or more from the non-treated group that are similar according to some characteristics. This requires a sufficiently large microdata set with a set of relevant control variables. Matching is appropriate for the analysis of a treatment on firms or households where 'treated' and 'control' groups have similar characteristics, except for the treatment itself. Of course, there must be a dataset available that has many observations alongside control variables.

Identifying the causal effect requires the analyst to control for all factors that may influence the decision to select into the 'treatment' or State aid program. This is a 'selection on observables' research design which means that, to implement PSM correctly, the selection into treatment must be completely determined by variables that can be observed by the researcher. Conditioning on these observable variables, the assignment to treatment is random. In other words, the pool of firms in the control group will be very similar to the treated ones in terms of the matched observable characteristics (except, of course, the treatment status), just as if the two groups were drawn at random before the assignment of the treatment. Large sample sizes result in a greater degree of precision in the matching procedure. If evaluators propose matching as the main statistical method to estimate the causal effect of an intervention, a series of sensitivity checks should be routinely performed (Box 3).

Box 3: Considerations when applying matching

a) assess the validity of the research design, as explained by Imbens and Rubin [8]. The research design's credibility would be reinforced if the impact of the treatment on the pre-treatment outcome is zero. This would imply that the assignment to the treatment is not correlated to the performance of the firm prior to the intervention;

b) divide the matching variables into two sets, and estimate the causal effect using a subset of covariates. If results are statistically different from those using the whole set of covariates, then one may cast some concerns about the validity of the research design;

c) ensure that the matching procedure is carried out on a sufficiently large number of firm characteristics that may explain both the outcome variables and State aid participation (also known as confounders), in order to discard potential alternative reasons that may drive the estimated results. Discussing these issues is particularly important because they are very context-specific;

d) test the robustness of the results to the use of alternative matching algorithms, to ensure that results are not specific to the chosen model only;

e) ensure that, after matching, there is an improved similarity alongside observable characteristics between the treatment and the control group (i.e. the two groups need to be "balanced"). This ensures that the matching procedure served its purpose and made the control group more comparable to the pool of treated firms.

Panel data methods (Fixed effects and Random effects)

Panel data are data that contain observations about different cross sections across time. A cross section could be a collection of individuals, countries or firms, with the same sample observed at two or more time intervals. Panel data methods allow for unobservable factors to be controlled for when quantifying the causal effect of a policy intervention.

Both fixed effects and random effects models are common. Random effects models assume that individual differences are considered random rather than fixed and estimable. It also requires the assumption that there is no correlation between the regressors and unobserved individual-level effects. This assumption is difficult to satisfy in many circumstances.

While fixed effects models require the assumption that individual differences are 'fixed' over time, the independence assumption is relaxed; the regressors may be correlated with unobserved individual-level effects. This is more plausible than the random effects assumptions in many circumstances. The fixed-effects estimator, however, can only then be used to estimate time-variant effects; time invariant effects will be filtered out by the estimation procedure. The Hausman specification test may be used to evaluate whether a fixed or random effects model is appropriate.

Matching may be paired with a fixed effects estimator to improve covariate balance and more closely approximate the result obtained under RCT conditions. It is argued that once the treated and untreated units are balanced on pre-treatment observables, the implicit assumptions of the fixed effects estimator are more plausible. Ferraro and Miranda[9] demonstrate how the combination of panel data methods with matching methods are often more likely to approximate a randomized controlled trial than applying a single design.

Difference in Differences (DiD)

Difference in Differences *(DiD)* compares the performance of a treated sample pre- and post-treatment relative to the performance of a control group pre- and post-treatment. The analysis allows treated firms/households to serve as their own controls. This approach is appropriate when there are factors that may influence the outcome of interest that may change with time, such as external macroeconomic influences. This is carried out by using trends in the control as the baseline[10].

In an energy context, the DiD approach is well-suited to estimate the causal effect of sharp changes in energy policies or practices, where the behaviour of a treatment and control group are expected to diverge through time. As with the previous approaches, microdata at the firm/household level is required and, in this instance, this data should be present for pre and post-policy intervention time periods. Alberini, et al. [11], for instance, use DiD to estimate the effect of an energy efficiency investment on household energy use. Using this approach allowed the analyst to control for the evolution of all other factors that may influence energy use. A simple before-and-after evaluation would not have sufficed in this instance as factors other than the treatment may influence the outcome over time. In addition, one cannot simply compare enrolled and unenrolled groups due to selection bias and differences in unobservable characteristics between the groups (B. Difference-in-differences overcomes both of these limitations.

One concern when applying DiD to energy-related investments is the issue of sample selection bias; there may be remaining unobserved characteristics leading to technology adoption or behavioural change by certain firms/households and this may bias results [12]. These are discussed in Box 4. Ideally, this would be overcome by using a strong instrumental variable. Since a valid instrument is not always available, a possible way to address potential endogeneity is the use of household (or firm)-specific fixed effects, as discussed by Alberini, et al. [11]. This is valid if any unobservable house or household characteristics that influence both the adoption decision and outcome of interest (e.g. energy consumption) are approximately constant over time. Box 5 discusses some considerations for practical implementation.

Box 4: Selection Bias

Liang, et al. [13] overview some potential sources of selection biases that evaluation of energy efficiency or household/firm-level installations should consider. For example, it is likely that the buildings with larger pre-treatment energy consumption (most likely less-energy-efficient buildings to start with) are more motivated to participate in an energy efficiency upgrade because their owners want to reduce their energy bills. These types of buildings have larger potential for energy reduction than the average building, which could lead to an overestimation of the treatment effects.

Second, environmentally-concerned participants are more likely to participate in energy efficiency programs. These participants might pay more attention to energy use post-treatment which would lead to overestimation of energy savings. On the other hand, it is also possible that these environmentally concerned people have already adopted some energy efficiency measures prior to a given intervention, leading to an underestimation of potential savings.

Box 5: Considerations when applying Differences in Differences DiD

When applying Differences-in-Differences (DiD) estimation the following checks must be carried out:

a) inspect the presence of pre-treatment trends in the outcome variables, given that this method identifies the causal effect of interest by assuming the existence of parallel trends before the intervention. This can be done visually (i.e. showing that the outcome variables evolve in parallel before the treatment) or statistically, using the procedure of leads and lags employed by Autor [14]. This is important even when DiD is performed with a control sample that is built through a matching strategy;

b) conduct, whenever possible, placebo analyses. For example, one could consider as treated a group of non-beneficiary or non-eligible firms and compare them to other non-beneficiary firms. The soundness of the research design would be strengthened with a finding of a zero "treatment" effect;

c) check that results are reasonably robust to the inclusion of additional control variables in the econometric specification.

Machine learning methods

Machine learning methods can be used to generate counterfactuals in panel data settings. To estimate the effect of an energy efficiency upgrade on school energy use, Burlig, et al.[15] use machine learning methods to specify a regression when the appropriate specification is not clear to the analyst. They use these methods to select the best forecast of counterfactual energy consumption in the post-treatment period.

Synthetic Control Method (SCM)

SCM are useful when it is difficult to find the perfect comparison group against whose outcomes the impact of the treatment can be measured. When evaluating the impact of a price support on renewable heating adoption, for instance, nearby regions or markets could be used as controls. However, geographic proximity is not necessarily the perfect counterfactual if there are substantial differences in political or cultural environments, while policies may spill across borders, confounding comparison[16].

Popularised by Abadie, et al.[17], the Synthetic Control Method (SCM) creates a synthetic control region that simulates what the outcome path of a region would be if it did not undergo a policy intervention. The SCM creates this hypothetical counterfactual region by taking the weighted average of pre-intervention outcomes from selected donor regions, such that the weighted pre-intervention path of the donor regions closely follows that of the treated region. This then acts as a control for the affected region following the policy being enacted. The difference in outcomes between the affected region and its synthetic control counterpart reveals the policy's effectiveness.

There are a number of important assumptions required for interpreting the SCM, outlined by McClelland and Gault[16], who also provide a useful guide on SCM implementation and evaluation. First, only the treated region must be affected by the policy change for all years in the pre-treatment period used to create the synthetic control and afterward. Second, the policy change has no effect before it is enacted. And third, the treated region's counterfactual outcome can be approximated by a fixed combination of donor regions.

While not used by many applications in the literature to date, SCM could be potentially used to evaluate a regional energy policy where a counterfactual is not readily available, but a number of comparison regions exist. This would be particularly useful at a sub-national level, should such variation exist, but may potentially be applied at the national level, should the required assumptions hold. The data requirements should be foreseen at the design stage of the scheme.

Regression Discontinuity Design (RDD)

Regression discontinuity analysis can elicit the causal effect of participation in a support scheme, such as a subsidy to support renewable heat, by comparing energy consumption behaviour on either side of an eligibility threshold. Under the assumption that household characteristics are randomly assigned in the neighbourhood of a threshold cut-off, the average treatment effect of the intervention may be identified. RDD requires a microdata source with sufficient observations in the neighbourhood of the cut-off for valid analysis (Box 6).

Boomhower and Davis[18] provide a useful guide on how Regression Discontinuity Design (RDD) may be used for programme evaluation. Many energy-efficiency programs have eligibility cut-offs which result in clear discontinuous changes in subsidy amounts. These thresholds can be used to measure infra-marginal participation (i.e. the change in participation as the subsidy for an energy efficiency upgrade increases from, say 30% of total costs to 50%). One can use observed changes in demand at various thresholds to infer what fraction of participants would have participated with no subsidy whatsoever.

RDD requires high-quality microdata at the level of adoption (e.g. firm, household). Treatment (i.e. program participant) and control (i.e. non-participant) groups are both required. For each observation, these data should outline program participation, the outcome variable of interest (e.g. technology adoption; energy consumption) and information relative to cut-off eligibility. For instance, household income is required if households are assigned the treatment below an income level. Similarly, energy usage is required if eligibility were based on passing an energy use threshold.

These data are not always readily available; however, there are many potential data sources that could be adopted. Gas or electricity network operators, private utility companies or energy management firms (e.g. providers of Google Nest and similar technologies) may have information on household energy consumption. Administrative data sources such as national registries may have information on income, should an income cut-off be considered. Combining such data with appliance installation may provide the suitable dataset (suitably anonymised to comply with data privacy requirements).

Box 6: Considerations when applying RDD

In the case of Regression Discontinuity Design, evaluators should make sure that:

a) households/firms are not able to manipulate the ‘assignment variable’ (e.g. the ranking). Roughly speaking, this means that beneficiaries cannot self-select (on purpose or unconsciously) on either side of the threshold. This is checked statistically by comparing the distribution of the assignment variable, which should be smooth at the cut-off. Manipulation is unlikely to occur in the case of grant programs (as it is not firms to decide their ranking), but it could be relevant, for instance, in the case of a tax break for firms below a certain dimension (firms may decide to “remain small” to enjoy the tax break);

b) the relationship between the outcomes and the assignment variable is well approximated by the statistical model used to fit the data and that results do not depend on how far from the threshold beneficiaries are: the larger the bandwidth (i.e. frame of analysis), the larger the number of observations (and the statistical precision) but the lower the comparability of beneficiaries;

c) the cut-off is unique to the program under analysis. For instance, if one wishes to evaluate foregone carbon emissions due to supports for low carbon heating, then researchers should ensure that no other policy kicks in at that same threshold, such as a grant for an insulation upgrade.

It is important to note that RDD gives a specific insight into the causal effect. As Boomhower and Davis (2014) discuss, RDD provides insight into the inframarginal change; that is, the change from one subsidy amount to another. It does not estimate the effect at the margin; that is, the change from zero subsidy to any subsidy. Boomhower and Davis (2014) show how this can be estimated, which an analyst may consult if required.

3.2.3. Second-best approach: counterfactual impact evaluation when data or context precludes (quasi-) experimental techniques

The previous sections outlined first-best evaluation techniques. Often, the assumptions and data requirements to carry these out are unavailable. A number of second-best options have been proposed in the literature. These should only be considered when it is unfeasible to carry out the first-best approach. Studies to date have employed a range of second-best approaches. For renewable energy supports, one may compare the share of renewable energy achieved using the State aid intervention with total renewable energy production. This provides a first indication of the importance of the State aid in the development of new renewable energy capacity. A financial analysis may also be carried out comparing financial return with and without receipt of grant funding.

Descriptive statistics, qualitative analyses and the analysis of renewable energy tenders are further second-best techniques that have been applied. Qualitative, descriptive methods are perhaps less preferable and a 'third-best' approach. While giving a broad indication as to intervention success, the additionality and proportionality is less clearly identified and not isolated as is the case for a causal analysis. Such qualitative approaches have taken the form of a purely qualitative survey, or a qualitative report, whereby installers were asked explicitly whether a policy had an influence on the decision to invest.

Checklist:

- Causal estimates provide the first-best outcome when eliciting the impact of State aid
- Randomised Control Trial is the gold standard when eliciting causal effects. This should be first explored. This requires an assumption of random assignment into treatment.
- Random assignment may be difficult for State aid policy, but quite feasible for policy adjacent activities, such as advertising campaigns. The possibility of such an experiment should be explored, preferably at the policy implementation stage
- Quasi-experimental techniques are an excellent substitute when an RCT is not feasible.
- Each technique requires specific data and methodological requirements. These should be assessed in the context of the policy in question when determining suitability
- Second-best approaches may be required but only when data are unavailable or methodological assumptions do not hold

4 Evaluating auction schemes

The preceding methods are often not available for the evaluation of renewable energy procurement auctions. This section will outline potential methods that may be used for such evaluation.

The objective of an energy procurement auction is to secure renewable electricity at least cost by overcoming an information asymmetry problem; a regulator may not always have the best information to set the correct, competitive price support, which can lead to excessive remuneration if set too high and underachievement of stated targets if set too low.

Given the information asymmetry, evaluation is difficult. The counterfactual cost of operation, the benchmark against which an auction outcome would be ideally measured, is by definition unavailable. In the literature, there are a number of approaches taken to evaluate an auction mechanism. First, one may seek to identify the appropriate design ex-ante. A wide theoretical literature exists with respect to optimal auction design. Analysts are referred to Maurer and Barroso[19], IRENA[20] and AURES II[21] for guidance on the design features for renewable energy procurement auctions. An evaluation report should first consider whether the design of the procurement auction is optimal relative to important contextual factors, some of which are listed in Box 7. If this is in order, the likelihood that the auction will procure renewable energy at least cost is maximised.

Second, studies have evaluated auctions by comparing prices, deployment quantities and other indicators of performance relative to a benchmark. While this does not allow one to identify how close the support is to the true cost of delivery, it allows one to evaluate offers relative to an alternative policy counterfactual, such as a fixed feed-in tariff price. One may also identify trends and performance relative to an (imperfect) estimate of costs, identifying whether policy costs track the cost of deployment. Finally, tender data may be employed in a supply curve analysis to consider a comparative static analysis of price and cost effects of an exogenous change in tender volume. These methods will be discussed in Sections 4.1 and 4.2.

Box 7: Guidelines for auction design

When designing an auction, a regulator must consider (i) what is the product being procured (e.g. energy or capacity); (ii) the auction process; (iii) the pricing mechanism; (iv) whether the auction is technology-specific or technology-neutral; and (v) whether there is to be a reserve price. Please see the evidence and guidelines accumulated by AURES II [21] for a full discussion of these factors. A brief discussion of pertinent points of analysis will now follow, followed by some further general guidelines.

The product being procured

The auction should directly procure the product that directly addresses the market failure. If there is a generating capacity constraint, such as an under-provision of flexible capacity by the market, then this should be a capacity (MW) auction. If the objective is additional renewable-sourced electricity, then units of energy (MWh) should be auctioned.

The auction process

There are many design features that must be decided upon. First, regulators may choose either a sealed-bid design or an iterative dynamic design, known as a 'descending clock auction'. Under sealed-bid auctions, bidders do not have information on other bids. Under descending-clock auctions, bidders react dynamically to other bids[22].

Each auction format has pros and cons. Maurer and Barroso [19] outline the process of a descending clock auction. The auctioneer begins the process by announcing a price that is considered high. Bidders reveal the quantities which they wish to offer at the stated price. If the quantity surpasses the procurement target, the auctioneer announces a lower price, and bidders reveal the quantities which they wish to offer at the new lower price. The process continues until supply meets demand, forming the clearing price.

A dynamic auction is suitable if there are high degrees of uncertainty surrounding product parameters or if the item being procured is subject to great degrees of risk. There is, however, an increased chance of collusion among bidders, who can use tacit signalling via bids to communicate, increasing auction prices and bidder profits [19]. Because of this, a sealed-bid auction is useful if the market is uncompetitive (See Shrimali, et al. [23] for a discussion of how to test for this) as it minimises the possibility of collusion. Further, the simplicity of the auctions lowers the costs of participation, bid preparation and auctioneer administration. However, there is a greater risk of over or underbidding due to weak price discovery and the 'winner's curse', whereby the winning bid(s) are below the market value.

In practice, auction designs routinely represent a hybrid structure, combining features of both sealed bid and descending clock auctions to meet policy objectives. Brazilian and Mexican auctions have taken this approach where an initial descending-clock phase allows for price discovery, followed by a sealed-bid one which prevents collusion. Since only a small number of bidders might be left in the auction as the price decreases, it is preferable to switch to a sealed-bid stage to minimize the chances of collusion and therefore reduce the final auction price as much as possible.[24] This also induces a higher participation rate (and probability of success) for small participants[22]. There is a range of potential mechanisms of varying sophistication which may follow this format. This auction is generally used when values are less well-known.

The pricing mechanism

Sealed bid auctions may take the format of a first-price, second-price or uniform price (i.e. pay-as-clear) auction. In a first-price pay-as-bid auction, the auctioneer selects the lowest bid(s), and the winner(s) receive(s) their bid price. A second-price, pay-as-bid auction (also known as Vickrey auction) occurs when the winner receives the price of the second most competitive bid, instead of their own bid price. If there are multiple items being procured, generalized second-price auctions exist where the winning bidder pays the second-highest bid, the second-highest bidder pays the third-highest bid, and so on. A pay-as-clear auction is applicable to a scenario where there are multiple winners and each winner receives the market clearing price.

Unlike a first-price auction, second-price auctions and uniform price auctions are incentive compatible as the bid does not affect remuneration upon winning. Pay-as-bid has been described as being more effective (i.e. leads to greater deployment) but uniform pricing can minimise the costs of support, since it is theoretically more incentive-compatible and has led to aggressive bidding in practice.[25]

Uniform pricing may face greater political pushback as all generators receive the same support, regardless of underlying cost structure. Irrational bidding is still possible under uniform pricing, however, as some bidders bid below their costs, hoping that the marginal bidder will set an attractive price for all winning projects [25,26], something observed in Spain and the UK [27,28]. In Spain, uniform pricing has contributed to many firms offering very low prices, believing that the cut-off point would be higher [25,27]. A uniform price auction attracts a greater number of small bidders, which aids competition in the post-auction market.

Technology-specific or technology-neutral

Technology specific auctions can help nascent technologies to grow. Similarly, spatially explicit auctions can incorporate spatial factors (such as network constraints or demand centres) into the auction design. Introducing these factors can facilitate potentially more expensive generation and divide the market, potentially reducing competition. These actions should be introduced with caution in smaller markets.

Reserve price

A reserve (i.e. maximum) price may help to limit the effects of poor competition and/or collusive behaviour. This should be high enough to reflect the policymaker's information regarding power plant costs.[19] This price should not be disclosed, however, with research finding that this usually biases the results of the auction. In South Africa and Peru,[22] it was found that bidders proposed relatively high bids which are marginally close to the reserve price. Auctions systematically clearing at the reserve price suggest a problem of undersubscription and potential overcompensation that would require to adjust the tender design, the volume on offer or the reserve price.

Further design features to note

Alongside the design features discussed, there are further design features which an analyst should consider when evaluating an auction design

There should be sufficient time between the announcement of the auction and the deadline for bid submission. This minimises the impact logistical factors may have on restricting participation and negatively affecting competition.[19].

Regulatory stability, transparency and perceptions of fairness are associated with positive outcomes[19].

Shrimali, et al.[23] found that this risk can be reduced if policymakers ensure more competition by auctioning a volume which is well within the market's ability to supply.

As del Río and Linares [22] discuss, strong penalties for non-compliance and deadlines for construction may counter under-delivery. Related to this, South African wind and solar auction offers were required to be underwritten by debt and equity investors as a prerequisite.

Predictable bidding rounds and longer price guarantees reduce risks for the investor[22].

Seller concentration rules can mitigate market power issues, if identified[22].

4.1. Auction schemes ex-post evaluation techniques

Ex-post evaluation of auctions has taken a largely descriptive or qualitative approach [22,29-33]. Rego and Parente [33], Butler and Neuhoff [30] and Bayer [29] are among those studies that carry out a qualitative comparison of auction prices. Rego and Parente[33] provide a regression analysis to identify whether there was a statistical difference in prices between auction schemes, controlling for confounding factors.

Shrimali, et al.[23] outline a quantitative approach when it comes to evaluating auction performance ex-post which may provide a useful framework. This is comprised of the following constituent analyses.

The comparison of auction results with policy benchmarks

First, the prices obtained during an auction are compared with prices/policy costs under an alternative benchmark such as a counterfactual feed-in tariff price. This may be a feed-in tariff previously imposed, a feed-in tariff from a nearby location or a ceiling price used in the auction. According to this procedure, an auction is considered somewhat successful with a 0-10% price reduction, successful with a 10-20% price reduction, and highly successful with a price reduction of more than 20%.[23]

Comparison relative to a breakeven benchmark

Second, one may consider the extent with which auction prices follow the estimated competitive price trajectory. Kylili and Fokaides[32] carry out such an analysis relative to a cost-effective breakeven price to track whether bid prices have followed estimated cost trajectories over time.

Comparison relative to a deployment benchmark

Shrimali, et al.[23] posit that an auction is considered successful on grounds of deployment if more than 75% of commissioned projects are built. An absence of difficulties in the planning procedure can increase deployment numbers, coupled with commitment devices so that developers cannot back out without consequence. Some evaluation reports to date have compared auction results relative to a benchmark cost. A discussion of auction prices relative to a benchmark can indicate whether policy costs are on a downwards trajectory. This can be difficult, however, if the trajectory is unclear due to potential confounding factors (e.g. changes in input costs).

Market concentration

A more competitive auction can lead to procurement closer to the cost of delivery, increasing the likelihood that any offered support is proportional. In practice, auctions have higher transaction costs relative to fixed-price mechanisms, due to planning and risk exposure. This may deter participation by smaller firms, resulting in a low degree of competition[22] and higher prices. In turn, this may eliminate the higher theoretical efficiency of this instrument. The Herfindahl-Hirschman Index (HHI) can measure competitiveness in the market and it is calculated by squaring the market share of each successful bidder in an auction and then totalling the resulting numbers. The U.S. Department of Justice posits that an HHI of less than 1000 is competitive, a score of 1000-1800 is moderately concentrated and a score of greater than 1800 is highly concentrated.[23].

Collusion risk

Shrimali, et al.[23] outline an additional method to evaluate collusion risk; the standard deviation of bid distribution. This operates on the assumption that the higher the concentration of bids, the more likely the risk of collusion. Artelys Optimisation Solutions[34] provide a comprehensive discussion surrounding market concentration to give insight into the degree of competition and therefore likelihood that a competitive price will be achieved.

4.2. Second-best approach using tender data

In the absence of adequate data for a comprehensive counterfactual impact evaluation, tender data from procurement auctions may be used to give insight into proportionality and additionality. These are second-best approaches when no alternative is available. First, a supply curve analysis may be carried out. By combining the data from submitted tenders, and ranking offers to generate in order of cumulative capacity, a supply curve may be formed. This can give a number of insights. The slope of the constructed supply curve or curves allows a comparative static analysis of price and cost effects of an exogenous change in the tender volume. Second, by combining data from numerous technology-specific auctions, it is also possible to assess what would have been the effect of a technology-neutral tender.

Specific features of the tenders should also be highlighted and analysed if relevant, e.g. the presence of zero-cent bids; the height of the bid cap; undersubscription/ presence of only a few bidders.

Checklist:

— A theoretical analysis of the auction design in the context of the application can identify whether the auction is well-specified and likely to be cost-effective.

— Ex-post analyses of auction outcomes allow performance to be measured against a benchmark.

— Tender data may be used to further understand the auction outcome

5 Indirect effects

5.1. Defining indirect effects

Indirect effects can be either positive or negative. In the context of energy policy, they can take the form of an effect that impacts a third party or an unintended effect that impacts the targeted party. Positive indirect effects often occur when there is a positive complementarity with other interventions. For instance, Schubert, et al.[35] find that energy audits have a direct effect (increased adoption of energy efficiency measures) and an indirect effect (increased likelihood of receiving financial implementation support, which in turn increases the rate of adoption of energy efficiency measures).

A review of the literature can help the identification of effects that should be considered for a particular context. Whenever a firm or household receives State aid, there is the possibility that this will change that firm/individual's behaviour in the analysed or related markets. Common indirect effects in energy markets include (but are not limited to):

Innovation

A policy that has the primary objective of increasing the rate of technology deployment creates additional innovation through *learning-by-researching* and *learning-by-doing.*[36]

Environmental emission

Policies that facilitate the adoption of renewable energy technologies or improve the efficiency of energy use often have environmental emissions reduction as the direct objective of the intervention. This may also be an indirect effect of other policies (see Box 8 for a full discussion).

Impact on markets for inputs

Price supports for the production of a given commodity may increase competition for inputs common to other commodities, such as steel. This can increase the cost of inputs for other goods and services, particularly in the short run as the capital infrastructure is fixed. In the long-run, production capacity may change to accommodate this change in demand.

Portfolio effects in the energy market

Least-cost energy delivery occurs as a result of a portfolio of energy technologies. Price signals, both in terms of the average price level and price volatility, helps guide the efficient portfolio to minimise prices and reduce volatility. Price supports dampen this signal, potentially leading to a sub-optimal portfolio of technologies (e.g. a feed-in tariff price guarantee for renewable energy shields investors from price volatility, dampening the incentive to invest in complementary storage or flexible generation technologies).

Distributional effects

Price increases will comprise a greater burden on lower income households and smaller firms as they represent a higher proportion of available resources. This may have social consequences that policy may wish to consider. For instance, if small firms are negatively affected to the extent that they must exit, this can impact competitiveness. There may be fewer firms in a market, increasing concentration and ultimately putting upward pressure on prices.

Behavioural rebounds

Certain impacts, such as increased energy efficiency, can lead to positive behavioural rebounds where households respond to insulation investment by spending the same or more on a warmer home, rather than reducing energy consumption.

Employment effects (both positive and negative)

State aid such as renewable energy price supports or renewable heat incentives can create jobs. These jobs should be considered net of the counterfactual jobs foregone (e.g. fossil fuel-related jobs) and the jobs lost through the distortionary effect of raising the subsidy through taxes (see next point).

The distortionary effect of raising revenues through taxation

For every euro raised through taxes, there is a greater amount lost due to the distortion in prices created in the economy. This can have a negative effect on employment and growth. Positive effects of subsidies should be considered net of this distortionary effect. See Barrios, et al.[37] for further information on quantifying these effects for various EU economies.

Subsidising otherwise underperforming firms

Government support to otherwise underperforming firms may lead to further distortion. The potential for this should be considered when evaluating a State aid intervention.

Carbon leakage

Policies designed to reduce emissions must consider the possibility that firms may export production of carbon-intensive goods to foreign jurisdictions where the cost of carbon emission is cheap. [38]

Checklist:

- Consider both positive and negative indirect effects.
- Ideally, identify all indirect effects that are likely to impact the measurement of the direct effect. The listed effects in this section comprise those most common and should be among those considered.

5.2. Quantifying Indirect effects

The methods used to quantify direct effects may also be used to quantify indirect effects. Indeed, where possible, the elicitation of causal effects through (quasi-) experimental methods is to be preferred.

A number of indirect effects has been analysed to date. The literature has considered the impact on transmission costs. Carbon emissions and impact on other energy-related policy objectives and/or spillover effects on other market participants have also been considered. Quantitative modelling has been employed to consider in many circumstances, with qualitative discussion also considered in many cases.

The causal impact of renewable energy deployment on other effects, such as additional employment is more difficult to quantify. Input-output and Computable General Equilibrium (CGE)-based methods[d] can provide a useful approximation. A common indirect effect is that of reduced CO_2 emissions attributable to the policy in question. There is an extensive research literature on the methods that may be employed to quantify this particular indirect effect, which is discussed in more detail in Box 8.

[d] Computable general equilibrium (CGE) models are a class of economic models that use actual economic data to estimate how an economy might react to changes in policy, technology or other external factors. As a general equilibrium model, they seek to explain the behaviour of supply, demand, and prices in a whole economy with several or many interacting markets, as opposed to analysing one single market in isolation.

Box 8: Estimating Marginal Changes in Emissions

The appropriate method to elicit the carbon dioxide attributable to a State aid policy intervention is predicated on the sector being assessed. Generally, there is greater availability of appropriate data and methods to estimate impacts in the electricity sector. Both ex-post statistical methods and ex-ante simulation methods are often used. Outside the electricity sector, CO_2 attribution often follows naturally from the calculation of policy "additionality".

CO_2 attribution for investments outside the electricity sector

Investments in areas such as renewable heat or energy efficiency upgrades (incentivized by policies such as the UK Renewable Heat Incentive or the Swedish Climate Leap programme) may follow the procedures outlined in Section 5 for calculating "additionality". Should "additionality" correspond to the additional renewable energy units consumed, relative to the counterfactual fossil-generated energy, then multiplying each by their emissions factors allows for a pre- and post- intervention change in emissions to be estimated.

Ex-post CO_2 attribution for the electricity sector

An ex-post statistical analysis elicits the avoided CO_2 emissions that are attributable to State aid-supported units of electricity generated from renewable sources. The quantity of emissions offset by renewable electricity depends on which kind of generation technology it substitutes for in the system, since the amount of emissions released into the atmosphere due to electricity generation varies according to the different types of power plants used to produce the necessary electricity. A number of methods exist to estimate the impact, with Cullen [39], Di Cosmo and Malaguzzi Valeri [40], Oliveira, et al. [41] and Kaffine [42] providing an outline of the statistical approaches that may be applied.

Cullen [39] outline a procedure that is most useful for estimating marginal changes in emissions when renewables are a small proportion of total generation. The estimation strategy is derived from the following rationale: the change in carbon dioxide emissions due to State aid intervention can be broken down into the change in emissions due to renewable energy generation times the change in renewable energy generation due to State aid intervention. Methods to estimate the change in renewable energy generation have been discussed in previous sections. To estimate displaced emissions, Cullen [39] describes a method whereby one uses data detailing electricity generation by generator for each time period to estimate the plausibly exogenous impact that wind has on that generator's output, conditional on factors that affect a conventional generator's decision to generate.[e] The data required for this analysis are available from many electricity market operators. Using this data, the average rate of displaced CO_2 emission per generator may be estimated per unit of renewable electricity generated. However, if it is likely that renewables penetration is high, or the system is small, such that the output of certain generators is being considerably curtailed or ramping occurs more often, then there may be bias in the estimates and an ex-ante approach may be more suitable[f]

[e] This estimation approach exploits the randomness and exogeneity of wind patterns to identify the average reduction in output for each generator on the grid due to wind power production. The diurnal and seasonal patterns of wind are not uncorrelated with other incentives for production by conventional generators. Therefore, the modeller must control for factors that affect a conventional producer's decision to generate electricity, which may also be correlated with wind power production. See Cullen 39 for a full discussion.

[f] There is some concern that applying average emission rates to offset production estimates may not give an accurate estimate of offset emissions. A generator's emission rate, although relatively constant for most technologies, can vary as a function of output level of the plant. This emission "bias" is documented in the engineering literature. If it is likely that renewables penetration is high, or the system is small, such that the output of certain generators is being considerably curtailed or ramping occurs more often, then there may be a greater likelihood of bias in the estimates. In such circumstances, ex-ante simulation methods may provide a more accurate estimate of avoided CO2.

This type of study using average emission rates implies that each fossil fuel-based plant is assumed to have a constant emissions rate, while in practice the marginal emissions rate of each plant varies along its range of output. In such circumstances, an analyst should favour a method that considers the variation in CO_2 emissions with output, using power plants' "heat rate curves". Such methods are employed by Di Cosmo and Malaguzzi Valeri [40] and Oliveira, et al. [41], among others. In these methods, the researchers first calculate the system-wide emissions by summing the emissions produced by each generator, taking into account the variation in emissions with output. The system-wide emissions during each period are then estimated, conditional on important factors. In a method similar to that of Cullen [39], one may estimate the average emissions attributable to a certain degree of installed renewables corresponding to the state-aid.

Ex-ante CO_2 attribution for the electricity sector

Often, state-aid may incentivise investment decisions. Structural models of electricity production are required to model both investment and operating decisions. In these modelling platforms, generating units are dispatched optimally conditional on demand and a renewables profile. Often, investment decisions are modelled. Provided the modelling infrastructure is available, these procedures are often easier to implement than ex-post analyses and are less exposed to bias. The PLEXOS power systems modelling software is a widely-used platform for applications such as this, but other frameworks are available or are sometimes developed by independent research teams. Clancy, et al. [43] use PLEXOS to estimate the emissions savings due to a high renewables' scenario. This approach may also be used to estimate effects such as the CO_2 avoided due to electric vehicle deployment[44] or the CO_2 avoided due to biomass or hydrogen electrolysis technologies[45]. These generation sources are 'dispatchable', i.e. the operators can decide when to generate, unlike wind or solar where generation is determined by the weather. Because of this difference, the methods used to estimate displaced emissions for wind and solar no longer hold.

Furthermore, these methods are especially useful for policy evaluation as (1) indirect impacts on other aspects of system performance are accounted for and (2) the requirement for a counterfactual is less of an impediment.

Checklist:

- Methods suitable for the quantification of direct effects may be applied when quantifying indirect effects.
- CO_2 reductions attributable to the renewable energy policy intervention is a common indirect effect and two primary methods exist: ex-ante estimation using models such as PLEXOS and ex-post methods using empirical methods.
- Ex-post methods are likely best suited to marginal changes in emissions, given required assumptions.
- For larger changes in emissions, an ex-ante model such as PLEXOS, which can account for structural changes in the electricity system, are likely most appropriate

6 Proportionality and appropriateness.

6.1. Calculating proportionality: methodological approaches

With respect to energy-related State aid, the measurement of proportionality differs with respect to the counterfactual of whether a certain degree of the targeted behaviour (e.g. renewable energy investment) would have happened regardless. Each potential counterfactual is discussed separately below.

Certain energy policies do not have a zero-deployment counterfactual, such as household-level energy efficiency investments.[9] (Quasi-) experimental methods may be employed to elicit the causal effect of policy on both proportionality and "additionality", subject to data availability. These have already been discussed.

When there is a zero-deployment counterfactual, such as when a renewable energy installation is not cost-effective unless the State aid intervention is in place, proportionality is more easily identified. A proportionate level of support corresponds exactly to the difference between deployment cost and that required for cost-effective deployment. Cost data are likely readily available. If data are unavailable, a qualitative analysis may be the only second-best option.

When there is a zero-deployment counterfactual, proportionality may be calculated through an analysis of financial viability. One may carry out a discounted cash flow analysis to estimate the Net Present Value (NPV), for instance. This is the sum of all associated costs and benefits, discounted to reflect the time value of money. The analyst may estimate production costs and market revenues throughout the lifetime of the project. Through this, they may identify the level of support that achieves breakeven with normal operating profits/return on capital [46].

Should a financial analysis conclude that remuneration is excessive, the analyst may wish to explore what is driving this. For tendered programs, there may be indications in the data as to potential driving factors. These could include factors such as undersubscription; tender design; a lack of candidate deployment sites; regulatory issues such as problems with permits and procedures. Section 4 and references therein provides further insight into potential design features that could lead to an uncompetitive outcome.

Data on capital and operating costs will be required to carry out a financial analysis. The analyst should note that the proportional return is predicated on the concurrent costs, such as capital and electricity costs, which will vary through time. Furthermore, these factors are subject to uncertainty and therefore the cost estimates are subject to error. To avoid offering windfall profits to investors, calculations will have to be updated regularly as estimated costs evolve. Dinica [46] provides guidelines for policy design in this respect, recommending that the evolution of specific cost levels and factors be monitored to locate 'sources of change'. For example, the cost of wind energy deployment is influenced by a number of constituent costs, such as capital, installation, operation and connection costs. Policy should monitor the evolution of these constituent costs and track the price support in proportion to any change. Alongside this, policy may need to track the undiversifiable risk exposure faced by the firm. The academic literature provides ways to evaluate such risk premia and a selection of this literature is discussed in Box 9.

[9] To identify whether the counterfactual is [approximately] zero, an analyst should consider whether investment is cost-effective absent any support. For some renewable energy technologies, this is clearly the case. For investments such as a retrofit of home insulation, which results in a lifetime cost saving, then the counterfactual is not clearly zero. Another aspect, which may inform this difference, is whether the market failure being addressed is an economic or behavioural/social/political failure. In the latter cases, an investment may be cost-effective absent any State aid support but a behavioural factor such as inattention or aversion to inconvenience may lead to under-investment.

Box 9: Risk and Renewable Energy State Aid

For many novel technologies, especially those with an intermittent generation profile such as wind and solar, investment risks may not be entirely hedged through traditional instruments. In such cases, support may need to include a risk premium. This is especially pertinent if a regulator is specifying the price support, and there is risk emanating from uncertain costs or remuneration that cannot be hedged by traditional instruments. A number of methods exist to estimate this risk premium.

Monte Carlo simulation methods may be applied to estimate the probability levels for achieving certain internal rates of return (IRR)[47,48] Gass, et al.[47] and Farrell, et al.[48] provide insight into how these methods may be applied. The concept involves specifying a distribution for each uncertain variable (e.g. electricity prices, output, uncertain input costs), with these values sourced from expert elicitation or the literature. A large number of simulations are drawn, accounting for any correlation between input parameters (e.g. the cost of components containing steel will be positively correlated). Each simulation iteration takes a random parameter from the distribution and a distribution of total costs may then be drawn.

Gass, et al.[47] and Bragg[49] suggest that if there is a negative Net Present Value (NPV) relative to a required 'hurdle rate', the underlying investment will most likely not be approved by management. The Monte Carlo simulation procedure estimates the probability that the IRR will exceed the hurdle rate, and be approved for deployment, under a set of market and price support conditions. It is the role of the policymaker to identify the degree of certainty with which they would like to offer this remuneration. Gass, et al.[47] use 90% and 95% thresholds using the Conditional Value at Risk (CvaR) method.

Alternative to the continuous updating of a price support, a policy can be chosen which automatically provide a proportionate level of remuneration. This may be achieved through a competitive auction, or a similar mechanism, whereby potential recipients of State aid compete for a finite number of supports (Box 10). Of course, successful realization of cost-competitiveness is predicated on the effective design of the auction mechanism and methods to maximise the likelihood of this ex ante, and evaluate the results of this ex post, are discussed in Section 4.

Box 10: Proportionality and appropriateness: examples from the literature

To date, evaluation reports consider proportionality in a variety of ways, with many following the cost-effectiveness guidelines suggested in this document. In many cases, Levelised Cost of Electricity[h] or Internal Rate of Return calculations provide a benchmark against which the proportionality of State aid remuneration may be identified.[i] These are often accompanied by a qualitative discussion, which may explain any drivers of change in such calculations.[34,50-52]

When applying the Internal Rate of Return (IRR) as part of a financial analysis, risk exposure is not explicitly considered. However, the calculated IRR can be compared to the likely 'hurdle rate'; a minimum rate of return required to incentivise investment, including an anticipated risk premium.

[h] LCOE; this is the discounted average cost of supplying one unit of electricity

[i] It should be noted that the LCOE concept has been abandoned in the Climate, Energy and Environmental Aid Guidelines (CEEAG) and Member States are asked to check necessity and proportionality of aid measure based on a funding gap analysis

Quasi-experiemental techniques can be used to evaluate proportionality when the counterfactual deployment scenario is not zero. As discussed in Section 3, the appropriate (quasi-)experimental method is data-dependent and predicated on the policy design. Nicolini and Tavoni[53], provide a particularly good guide on how marginal effects can be evaluated which may be used to inform proprotionality and appropriateness. Should a policy have a stepped incentive pattern, whereby the amount of remuneration is conditional on a given running variable such as energy consumption, then this may be exploited using Regression Discontinuity Design (RDD), following the approach of Boomhower and Davis[18]. These quasi-experimental techniques can identify the additional deployment due to a marginal change in State aid. One can then use this information to calibrate the level of State aid to that required to achieve the policy target.

Checklist:

- When the counterfactual is clearly zero, proportionality may be calculated according to the rate of return on investment.
- If technologies are novel and costs/revenues are subject to considerable uncertainty, this should be considered in the evaluation to minimise the change of underachieving deployment targets
- When there is a non-zero-deployment counterfactual (e.g. household-level energy investments), then (quasi-) experimental methods can often exploit policy design features to elicit the causal effect.

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8 Glossary of terms

Combined Heat and Power: Power station that produces both electricity and heat.

Computable General Equilibrium: Computable general equilibrium (CGE) models are a class of economic models that use actual economic data to estimate how an economy might react to changes in policy, technology or other external factors. As a general equilibrium model, they seek to explain the behaviour of supply, demand, and prices in a whole economy with several or many interacting markets, as opposed to analysing one single market in isolation.

Conditional Value at Risk (CVaR): Measure of risk exposure, used in the field of financial risk measurement to evaluate the market risk or credit risk of an investment. It is calculated as the expected return on the portfolio in the worst x% of cases.

Difference-in-Differencea (DiD): DiD compares the performance of a treated sample pre- and post-treatment relative to the performance of a control group pre-and post-treatment. The analysis allows treated properties to serve as their own controls, controlling for factors that may change with time, such as external macroeconomic influences by using trends in the control as the baseline[10].

Externality: An externality is a cost or benefit caused by a producer or individual that is imposed on a third party. An externality can be both positive or negative and can stem from either the production or consumption of a good or service. Externalities can be private (incurred by an individual or firm) or social (affecting society as a whole). Unpriced carbon emissions are an example of a negative externality. The reduced transmissibility of a virus due to vaccination is an example of a positive externality.

Hurdle Rate: A hurdle rate is the minimum rate of return on a project or investment required by a manager or investor. It allows companies to make important decisions on whether or not to pursue a specific project. The hurdle rate describes the appropriate compensation for the level of risk present—riskier projects generally have higher hurdle rates than those with less risk.

Instrumental Variable (IV): An instrumental variable is a third variable introduced into regression analysis that is correlated with the predictor variable, but uncorrelated with the outcome variable. By using this variable, it becomes possible to estimate the true causal effect that some explanatory variable has on a outcome variable.

Internal Rate of Return: The internal rate of return (IRR) is a metric used in financial analysis to estimate the profitability of potential investments. IRR is a discount rate that makes the net present value (NPV) of all cash flows equal to zero in a discounted cash flow analysis.

Levelised Cost of Electricity (LCOE): This is the discounted average cost of supplying one unit of electricity in units of €/kWh.

Market failure: A market failure is a situation in which the allocation of goods and services by a free market is sub-optimal, often leading to a net loss of welfare.

MegaWatt (MW): Unit of power. Often used in relation to the capacity of electricity generating plant.

Megawatt-Hour (MWh): One megawatt-hour is equal to one megawatt of electricity geing

Net Present Value (NPV): NPV is net sum of payments and revenues. Future payments and receipts are discounted according to an appropriate discount rate. The NPV calculation finds today's value of a future stream of revenue and payments.

Propensity Score Matching (PSM): The propensity score allows one to design and analyse a nonrandomised study so that it mimics some of the particular characteristics of a randomised controlled trial. In particular, the propensity score is a balancing score: conditional on the propensity score, the distribution of observed baseline covariates will be similar between treated and untreated subjects.

Quasi-experiment: A quasi-experiment is an empirical interventional study used to estimate the causal impact of an intervention on target population without random assignment. Often, specific empirical strategies are employed to identify causal effects with the absence of randomisation.

Randomised Control Trial (RCT): A randomized controlled trial is a form of scientific experiment used to control factors not under direct experimental control. By randomly allocating participants among compared treatments, an RCT enables statistical control over these influences. Provided it is designed well, conducted properly, and enrols enough participants, an RCT can isolate the causal effect of a treatment (e.g. state aid support) on an outcome (e.g. renewable heating installations).

9 List of boxes

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