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Abstract

Clean energy innovation is pivotal for low-cost energy sector decarbonisation. Substantial public research and development funding is spent on energy innovation. Generating more evidence on which support mechanisms most effectively drive clean energy innovations, and why, could improve their design moving forward. In this *Perspective*, we discuss five challenges that researchers often face when attempting to rigorously evaluate energy innovation policies and public subsidy programmes. We recommend solutions, such as developing new innovation outcome metrics that consider unique features of the energy sector and building databases that cover long time periods. We also suggest that researchers and funding agencies work together to implement randomised control trials or conduct quasi-experimental evaluation of existing programmes and policies wherever possible.

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I. Introduction

Twenty-four countries and the European Union committed to double public spending on clean energy research, development, and demonstration (RD&D) by 2021 through "Mission Innovation". According to reported figures, investments are increasing, but they are still falling short of targets[1]. The success or otherwise of this spending in driving innovation is likely to have a significant impact on the overall costs of reducing greenhouse gas emissions. Ensuring that these scarce resources are not wasted requires designing policies and public support programmes based on evidence of what mechanisms actually increase innovation. Indeed, governments are increasingly demanding this; the *Foundations for Evidence-Based Policymaking Act* of 2018 provides an example of the trend in the USA.

Yet the evidence on what works best, and why, is surprisingly limited. Policymakers might start by looking at evaluations of previous support schemes, but the findings so far are limited and mixed. A 2015 review by the What Works Centre for Local Economic Growth of 1,700 papers on the impact of direct funding for innovation identifies 42 that use rigorous statistical methods[2]. The review examines papers studying the impacts of direct funding for any sort of innovation (i.e., not just energy innovation, which would result in a more limited literature). Figure 1 plots the results of the 42 studies assessed plus two papers that have been published since the review (see Supplementary Data for a list of citations), showing the number of papers that find positive, mixed, zero, or negative impacts of direct funding on innovation inputs, outputs, and outcomes.

The main takeaway is that there is no clear conclusion regarding the effects of direct funding programmes so far. There are several potential explanations for this. For instance, different programme design features could impact effectiveness. Some metrics for capturing outcomes also might be inadequate, or analyses might not allow enough time to pass before assessing impact. There is also heterogeneity amongst firms and industries that is masked by measures of average effects. Continued work is needed in order to better understand how public resources can cost-effectively foster innovation.

[FIGURE 1 ABOUT HERE]

In this *Perspective,* we develop a framework for energy innovation evaluation. We highlight five reasons that generating robust evidence of what policies and programmes are most effective is so challenging, and we identify potential solutions. Overcoming these five challenges is critical for improving programme and policy design moving forward, as the resulting analyses could provide insight on which mechanisms deliver and under what conditions.

II. Summary of The Five Challenges

The first challenge is quantifying how much of innovation activity can be attributed directly to the policy or programme as opposed to other factors (i.e., the "causal effect" of public support on outcomes). It is difficult to find a valid counterfactual—a control group—to examine what would have occurred without funding. However, econometric methods that allow for causal inference can be applied to evaluate high-level policies and programmes, like grants awarded by federal agencies or tax incentives, as well as more narrow efforts, like Canada's Sustainable Development Technology Funds, Europe's Climate-KIC, and the U.S.'s Cyclotron Road.

Second, there are significant and uncertain time delays that occur in the energy sector between funding and technology development. Tracking long-term financial flows to energy technology innovation and trends in energy RD&D investments is therefore important[3,4,5,6,7]. Doing this at a micro-level could enable even more detailed analyses. To this point, the National Academy of Sciences conducted a comprehensive assessment of the U.S.'s flagship Advanced Research Projects Agency-Energy (ARPA-E)—established in 2009 to fund energy projects—and concluded that, while ARPA-E made progress toward achieving its mission and goals, it needs a framework to analyse outcomes for at least 10 years post-funding to fully capture programme impacts[8]. Another option is tracking intermediary outputs that are correlated with final innovation outcomes.

Third, while *inputs* into the innovation process—such as an entity's spending on energy R&D—can be reasonably measured, capturing information on *outputs* (whether innovation actually occurs) and *economic outcomes* (whether the results are beneficial to the organisation or economy) is less straight-forward. Researchers often use measures like publications and patents to proxy for innovation outputs, but new metrics are needed. For instance, project outcomes from specific programmes can be documented—as they were for ARPA-E in the past[9]—and collated systematically within and across programmes in an accessible database.

A fourth challenge is in distinguishing the *direction* of innovation when assessing these outputs to account for whether the innovation advances clean versus dirty technologies. Lastly, as governments often implement numerous policies and programmes simultaneously, it is important to disentangle the effects of each in order to optimally design policy.

These five challenges are also present in other sectors, but unique characteristics of the energy sector make them particularly pressing here. For instance, there is a double-externality challenge[10]. Firms do not fully appropriate the benefits of their innovations due to knowledge spillovers, while local environmental pollution generated by the energy sector remains inadequately priced. Clean energy innovations also have much larger knowledge spillovers relative to the average technology due to their novelty, even before accounting for the environmental externalities[11]. More spillovers justify higher levels of public funding.

Another unique feature is that energy is a commodity, rendering many of the traditional metrics for studying innovation less useful. In addition, developing new energy technologies is capital-intensive and requires uniquely long time horizons for verification and validation. This imposes significant investment risk and has contributed to difficulties with the traditional venture capital model for cleantech[12]. Energy innovation policy should also be conscious of technology "lock-in"—when an incumbent technology drives out others that could be superior—which can be exacerbated depending on policy design[13]. Some clean energy technologies, like crystalline silicon solar PV and lithium ion batteries, are arguably near the point of lock-in. Finally, the stakes are high because of the nature, scale and time horizons associated with climate change, which poses urgent threats to human civilization.

III. Significance of Programme and Policy Evaluation

The economic rationale for public spending on innovation is well-known. Without government intervention, competitive markets under-incentivize private investment in the development and diffusion of new technologies[14,15]. Society accumulates knowledge spillovers from R&D, which firms do not incorporate into their innovation investment decisions[10]. This creates a wedge between the social and private benefits of innovation that policymakers should seek to eliminate[16].

Ramping up public spending on clean energy R&D does not guarantee successful innovation, however. Spending wisely is key to ensuring that the intended outcomes are achieved cost-effectively. Policy makers can use a wide array of instruments, from direct grants that target specific technologies to tax credits that reduce the cost of R&D. Grant-making agencies can target basic versus applied research. Tax credits can be volume-based, incremental, or both, and so on.

IV. Challenges and solutions to impact evaluation

This section discusses in detail the five challenges and potential solutions for evaluating clean energy innovation policies and support programmes, which we summarize in Table 1.

a. Quantifying Causal Effects

One approach to rigorous evaluation is measuring the "causal effects" of programmes and policies (i.e., the additional innovative activity that results as a direct response to the intervention). Estimating causal effects isolates the marginal effect of the intervention, stripping out the impact of other factors that may impact outcomes and lead to inaccurate conclusions. It uses counterfactuals to compare outcomes after entities receive public support relative to potential outcomes that would have occurred *without* support. However, potential outcomes from funded entities had they not received funding are not observable by definition, and thus finding convincing counterfactuals is difficult. One option is to assess outcomes from those receiving funds (a "treatment" group) against outcomes from comparable entities who do not (a "control" group) using regression methods.

There are at least two statistical challenges to address in order to interpret findings as causal. First, "selection bias" affects the difference in outcomes if entities receiving funding differ systematically from those that do not[17]. For example, firms that are already more innovative may be more likely to apply for and win grants. This biases a direct comparison of the two groups' outcomes, since it incorrectly attributes differences fully to the funding rather than other firm characteristics[18]. Note that we do not mean the project selection process is biased, but rather, there is a statistical "selection bias" due to the underlying differences across the two groups.

Second, "simultaneity bias" complicates these types of analyses. Policies supporting innovation often coincide with other trends that impact innovation. For example, firm investments in specific energy technologies may be driven by expectations about government or society favouring those technologies. Yet governments may increase funding for those technologies if it is of political and social interest. Both funding and wider trends likely influence firms' research efforts.

A suite of econometric methods allows researchers to quantify "causal effects" that remove these biases. The gold standard is to implement randomised control trials (RCTs): carefully designed experiments that test a hypothesis by randomising treatment, much like experiments in other scientific research. Perhaps for good reason, RCTs have been rare in innovation studies—much less energy innovation—despite their increasing use in other subfields of economics and policy analysis[19,20]. Randomising the allocation of innovation support itself may not be an attractive option, as it could undermine expertise developed over many decades that informs funding decisions. However, there are other ways in which RCTs can be used innocuously. Section V provides explicit examples.

At the same time, embedding other forms of "randomness" that mimic experiments offers a powerful alternative while imposing less risk. These features already exist in some cases. For example, agencies can set cutoffs in firm size or other firm characteristics when setting funding rates (e.g., Innovate UK currently does this, funding 45% of proposed experimental development projects for "small" firms versus 35% for medium-sized firms). If the cutoff for what defines "small" is set arbitrarily, firms receiving grants just below and above the firm size cutoff are likely similar on many dimensions, with the exception of the funding rate. Comparing outcomes between these two groups, therefore, provides indication of the additional benefits incurred from the more generous funding rate. Implementing a regression discontinuity design using a threshold like this allows for funding effects to be interpreted as causal[21]. To be clear, we are not suggesting that the decision to fund a project should be randomised, but rather, once projects are selected, funding rates could differ.

Innovation funding programmes often generate forms of randomness like this but researchers face data restrictions. For instance, an expert review panel often grades or ranks funding proposals as part of the review process, and funding decisions are determined by a cutoff in the grades or rankings. The cutoff is typically implicit based on the total amount of money available, but one can infer where it is with information on scores for all proposals and knowing which proposals win. Firms that fall just below this cutoff (and do not receive funding) may be a convincing control group for studying the impact of funding on firms just above the cutoff (receiving funding).

A handful of recent studies use approaches like this to analyse R&D support. One paper examines the U.S. Department of Energy's Small Business Innovation Research (SBIR) programme and finds large, positive impacts of direct grants on patents, revenue, and the probability of subsequently receiving venture capital[22]. It also distinguishes between clean and dirty innovation, showing that R&D subsidies spur clean innovation but not innovation in conventional energy technologies. Other studies of innovation broadly use similar methods[23,24,25,26,27].

Another approach is to use matching methods to compare entities that receive funding with "similar" entities that do not, but this does not entirely address the problem. Characteristics for which there is no data cannot be used in the matching. For example, the researcher may have information on a firm's size, previous R&D spending, financial performance, etc., and can use this information to match firms to similar firms that do not receive funding. But other factors that are difficult to measure yet impact outcomes, like management quality, remain ignored.

Instrumental variable (IV) methods also can remove statistical biases. This entails finding a variable that strongly predicts whether a firm receives funding but does not directly affect the outcome. Some innovation studies have implemented this approach[28,29,30]. It can produce unbiased results, but finding valid IVs is notoriously difficult.

Finally, the simplest (but typically insufficient) approach is to include variables that "control for" other influences on the outcome. If the analyst has data on firm characteristics that affect the propensity to innovate, for instance, including these variables in the regression equation reduces some of the bias. However, it is difficult to know whether a set of control variables adequately captures *all* of the relevant information.

b. Accounting for Response Timing Lags and Uncertainty

There is a time lag between research support and commercial outcomes, which makes it difficult to measure the final impact of funding[30]. Time lags are particularly long for legacy sectors like energy[32]. Recent work has shown that more than a decade is needed to realise the full effect of public energy R&D funding: the first new patent applications typically appear within about one year but they continue for roughly another 13 years[33]. Patents even may be considered intermediary outcomes, and the development of new energy technologies can take decades.

This suggests that studies limited to the years immediately following funding will under-estimate effects, not just on actual technology commercialisation but also patenting. Extending sample periods to include many years can help. This requires tracking firms and outcomes over long time periods[8]. Analyses over longer time periods, in turn, must account for other trends and changes that impact outcomes over time.

Earlier stage progress can be measured in the meantime by examining the impact of funding on intermediary outputs. Doing so is particularly helpful when there is a known correlation between some intermediary outputs and final outcomes, and thus a first order research question is what intermediary outputs are strongly correlated with technology development, deployment, and diffusion. Researchers commonly use patent data to evaluate energy R&D[33,34,35,36,37,38], but publications and their citations likely emerge in a shorter amount of time post-funding[33]. Do publications predict patents in the energy sector? Do patents predict product launches? Are there other intermediary outputs that better predict technology commercialisation? Tracking energy technology performance, like costs and capacity factors, can capture incremental innovations. The National Renewable Energy Laboratory's recently-launched product performance database may foster such research.

c. Measuring Level and Quality of Innovation

Measuring innovation outcomes (e.g., technology advancements) as opposed to innovation inputs (e.g., a firm's R&D spending) is inherently difficult. Traditional innovation measures also may not be suitable for the energy context since energy is a commodity. Surveys conducted in many countries ask firms about their innovation activities, such as whether they made new or significant improvements to a product, service, or process. The resulting datasets provide consistency over time but rely on subjective reporting and provide minimal detail.

Researchers also often use detailed proxies like patents or publications[11,26,33,37,]. However, these are arguably intermediary outputs, signaling that a company has valuable assets but without guaranteeing that this translates into innovation. Patenting may be a particularly poor proxy for innovation in energy moving forward given the increasing demand for renewable energy integration and smart technologies. Related innovations may be classified as advancements in information and communications technology—and thus not captured by algorithms identifying only energy patents—yet such advancements may impact grid management. Intellectual property protection strategies and norms also vary.

New measures of innovation that reflect the sector's unique features are needed. For example, as speedy commercialisation is a pressing challenge for cleantech, using data on product launches could be used to assess how quickly firms bring their innovations to market. Metrics should distinguish between improvements on existing technologies versus entirely new solutions and account for innovation quality by weighting innovation rates by market impact. Market diffusion can be measured through end-use adoption, which has been done for solar PV markets. Firm performance metrics like profits, survival, and private finance secured could shed light on economic outcomes[22,39,40,41]. One could look to other established technology development programmes for ideas, such as the U.S. SBIR, which is often considered a pioneer in technology evaluation and provides useful public workshop documentation.

d. Distinguishing the Direction of Innovation

An important nuance to studying energy innovation is capturing the *direction* of technological change[42,43]. That is, if funding increases innovation activities, is the effect stronger for clean versus dirty energy? Mission-oriented grant schemes may steer innovation in ways that other mechanisms, such as fiscal incentives, do not. Mission-oriented policies aiming to tackle societal challenges like the clean energy transition can incorporate both coordinated public investments as well as market-shaping policies[44]. However, even if support policies apply broadly (e.g., tax credits available to all firms investing in R&D), certain types of entities may respond differently.

Some recent work is addressing this by examining the impact of renewable energy policies or by classifying energy patents as clean or dirty. For instance, the impact of renewable energy policies on patent counts has been studied[37] and an examination of the SBIR grant programme distinguishes between energy technologies[22]. One of the most thorough treatments of this issue so far constructs a firm-level dataset on the auto industry and shows that firms facing higher fuel prices innovate more in clean technologies[45]. More research like this is needed.

e. Examining Policy Interactions

A final challenge is accounting for programme and policy interactions. This includes support schemes with similar objectives as well as those with different objectives but which simultaneously impact the same entities. Disentangling the independent effects on organisations receiving multiple subsidies is non-trivial. For example, while direct subsidies for specific renewable energy technologies aim to accelerate innovation, environmental policies such as carbon taxes also generate incentives for the development and diffusion of relatively clean energy technologies by changing relative prices. Understanding whether these policies are complementary is important for optimal policy design and ensuring the cost-effectiveness of public spending.

A critical area for continued investigation therefore is policy instrument choice and evaluating interactions when there are multiple policies and market failures. Some studies using simulation methods address this[47,48]. Quantifying the causal effects of overlapping policies is rare.

[TABLE 1 ABOUT HERE]

V. Policy Recommendations & Research Priorities

We have laid out five challenges that, in our view, must be overcome in order to generate a wider evidence base of clean energy R&D funding and policy effectiveness. Removing barriers that contribute to these challenges could enable researchers to marshal robust evidence on what works and why, which can be used to improve energy innovation programme and policy design moving forward.

Governments and grant-making agencies can reduce these barriers in several ways. At the least, tracking successful and non-successful applicants enables researchers to compare firms that receive funds relative to firms that are similar but do not receive funds. This information can be linked to other data to assess the resulting innovation activity, and covering long time horizons permits evaluation of both short- and long-run effects. A few related database efforts are underway. The University of Michigan's Institute for Research on Innovation & Science is collecting administrative data on research investments. Star Metrics is also creating a data repository of the inputs, outputs, and outcomes resulting from U.S. federal investments in science. Accounting for whether innovation outcomes are environmentally-friendly will remain critical for assessing the *direction* of innovation.

Government officials can also support implementation of quasi-random experiments or innovation RCTs. Some science funders are actually allocating money randomly through grant lotteries already[49]. However, there are also other ways that randomisation can be used if there is concern that complete randomisation would undermine the project selection process while still allowing researchers to uncover what support mechanisms work best. The Innovation Growth Lab is funding more than 50 RCTs on innovation, entrepreneurship, and growth[50].

One possibility for the energy sector is to randomise certain requirements attached to grant funding (once grant recipients are selected), such as collaboration with specific types of firms, national laboratories, or universities. Combined with improved outcome measures, such as cleantech start-up product launches or intermediary outputs that are correlated with innovation diffusion, this can reveal whether collaborations affect commercialisation.

Some “quasi-experiments” are already embedded in existing policy and programme designs but the information or data to study them are not readily available. Grant-making agencies often have procedures for grading or ranking project proposals, and either explicit or implicit cutoffs determine which projects are funded. Comparing outcomes of firms that fall just above and below these thresholds mimics an experiment, as these firms are likely similar on other dimensions. This type of method has been used successfully already[21,22,24,25]. One critical requirement of this approach is access to proposal grades or ranks, including those for unsuccessful applicants, and thus we encourage grant-making agencies to continue enabling researchers to access data like this.

Finally, through our review of the literature, we identified research areas that remain under-studied but which seem critical for developing a better understanding of how to drive clean energy innovation. First, focusing on how organisations respond *heterogeneously* to the same support mechanisms could uncover information about what types of mechanisms work best for certain types of firms or under different conditions. Second, estimating the persistence of effects over time could provide insight into “behavioural additionality”. That is, whether there are longer-run changes to organisations’ strategies, capabilities, and management practices that continue to enhance innovation outputs and productivity. Third, not all innovations are created equally. Some mechanisms may work better when it comes to enhancing an innovation’s *value* or steering innovation towards protecting environmental systems rather than harming them. Fourth, clean technology policies and incentives often interact with environmental policies and regulations, such as carbon pricing. How organisations respond to such interactions is not well-understood. Lastly, innovation has the potential to help drive economic growth, productivity, and development. Further study on whether such impacts vary between programme and policy design, or for innovation in clean energy relative to dirty energy or other sectors, could shed light on the wider socio-economic implications of energy innovation support.

Rigorous evaluation of innovation programme and policy evaluation is essential for developing evidence-based clean energy innovation policy. We focused on data-driven solutions. Nonetheless, there are limitations associated with using these methods, as there are with any approach. Three to keep in mind include: 1) many variables impact a firm's innovation capacity, and controlling for these is important, especially without an experimental setting, 2) investigator bias may shape research questions and the outcomes studied, and 3) technical expertise is still needed to identify what inputs and outputs are most relevant.

Overcoming the five challenges would lead to a significant increase in the evidence base of policies that can successfully drive innovation in the energy sector, at a time when such innovation has rarely been more important for humanity.

Data Availability

Please see the Supplementary Data file for the list of papers used to create Figure 1.

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Author Contributions

All three authors contributed to the writing of this paper.

The authors declare the following competing interests:

Cameron Hepburn is the Director of Aurora Energy Research Limited, an energy analytics firm, Vivid Economics Limited, an economics consultancy firm, has several clients in the energy sector and has had academic funding from Shell.

Figures

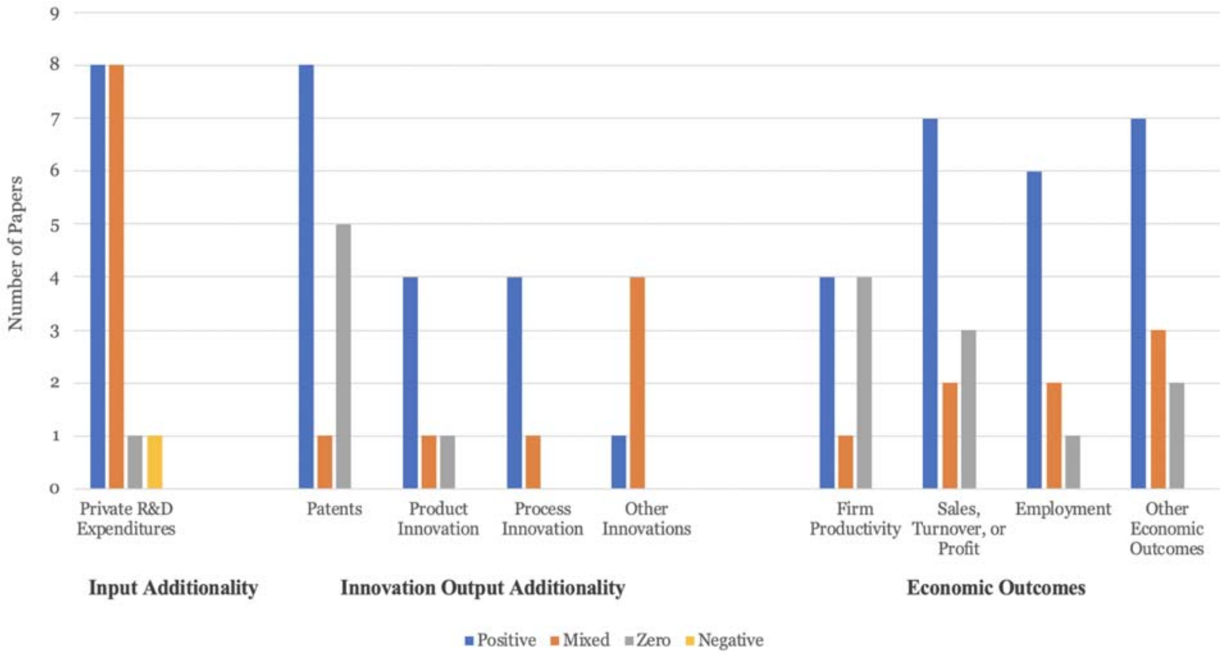

Figure 1: Evidence on spending, innovation, and economic outcomes

Note: This figure plots the number of papers finding positive, mixed, zero, or negative effects of direct funding for innovation on innovation inputs, outputs, and outcomes. It includes papers covered in a review by the What Works Centre for Local Economic Growth in 2015[2] and two additional studies published since the review[22, 23, 25, 39, 41, 51-89].

Tables

Table 1: Major Challenges and Solutions for Evaluating the Effects of Public R&D Support

Challenge	Description	Examples of Solutions
1. Quantifying Causal Effects	Studies of innovation support mechanisms are prone to selection and simultaneity biases, making it difficult to tease out effects directly attributable to the policy or programme.	Employ research designs that allow for causal inference. Work with grant-making agencies to embed quasi-experiments into incentive design, find "randomness" that already exists, or conduct randomized control trials (RCTs). In these efforts, focus on the innovation challenges that are unique to clean energy to generate sector-specific recommendations.
2. Accounting for Response Time Lags and Uncertainty	There are long and uncertain time lags between receiving support and producing measurable innovation outcomes.	Collect and use data on outcomes spanning long time periods post-programme or policy support. For example, in order to fully capture the market and innovation impacts of ARPA-E, a streamlined reporting process should be maintained for many years.
3. Measuring Level and Quality of Innovation	Measuring innovation is non-trivial and data for doing so are often difficult to access. Traditional metrics may not be suitable for the energy sector, and moving forward, patents may become less suitable. Quality of innovation is also important given the vast heterogeneity in the impact of innovations.	Develop measures of innovation that account for unique features of the energy sector, such as cost reductions or operational and efficiency improvements. For example, examine cleantech product launches or electricity generators' profitability. Capture the *quality* of innovation by weighting innovation rates by market impact.
4. Distinguishing Direction of Innovation	Distinguishing innovations based on whether they are in clean or dirty sectors develops a better understanding of how policy steers the *direction* of innovation.	Exploit detailed data and develop new databases that specifically capture whether innovations are environmentally-friendly. Account for these differences when assessing outcomes. Organisations and their innovations must be identifiable as being associated with clean versus dirty energy technology or services.
5. Examining policy interactions	There is a wide array of funding programmes and policies that support innovation directly as well as non-R&D types of policies and regulations that indirectly affect the energy sector, such as carbon pricing.	Identify empirical settings where funding allocation rules across support mechanisms and other non-technology policies that affect relatively clean innovation do not align so that the independent and interaction effects can be quantified. For instance, study how

	Disentangling their independent effects and quantifying the impact of their interdependence is non-trivial.	technology and environmental policies affect clean energy innovation outcomes, or examine whether layering multiple funding mechanisms is cost-effective.