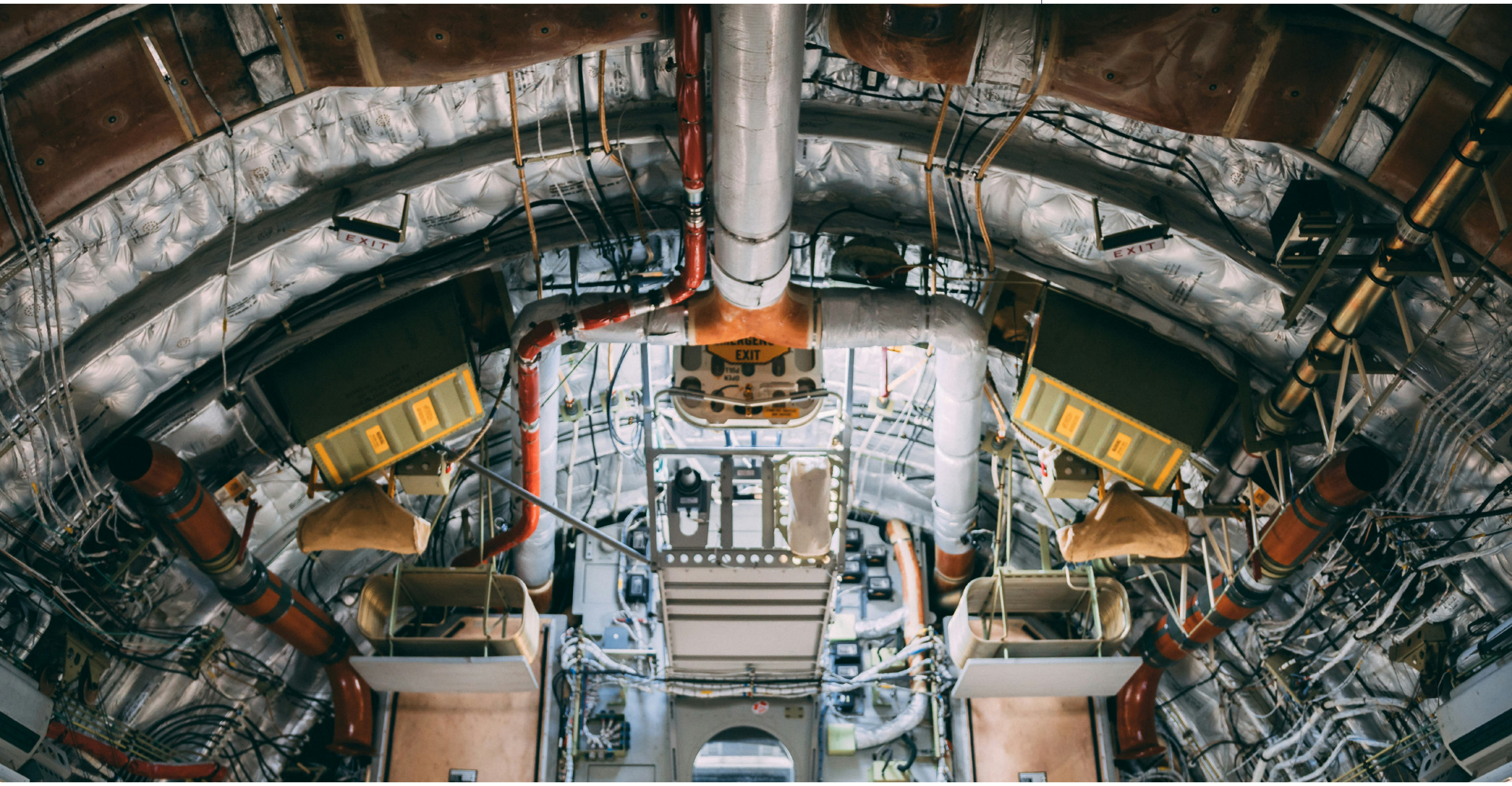
Investing in Innovation to Cut Energy Costs and Emissions

The Role of Public Research and Development Spending

by David Kemp

March 2026



Introduction

Energy policy in the United States stands at a crossroads. Although U.S. greenhouse gas emissions have declined substantially since their peak in 2005, much of this decrease represents a market-driven shift from coal to inexpensive shale natural gas.[1] Some evidence suggests that emissions reductions have stalled in recent years.[2] Globally, it is increasingly clear that the goal of limiting warming to 1.5°C, as set out in the 2015 Paris Agreement, is unlikely to be met.[3]

At the same time, energy affordability, especially rising retail electricity prices, has become a politically charged issue in the United States. Policymakers from both parties frequently attribute higher prices to each other's preferred energy sources or policy approaches.[4] In reality, the drivers of rising energy costs are complex, but growing electrification, the rapid expansion of data centers and AI, and substantial investment needs in electricity infrastructure all suggest additional upward pressure on electricity prices in the years ahead.[5]

In this context, it is critical to assess the policy mechanisms available that could reduce energy costs and lower emissions. Climate policies that directly or indirectly raise energy prices, such as carbon taxes or stringent regulatory standards, face political resistance and undermine efforts to improve energy affordability. Other policies, such as tax credits for mature technologies, can carry high fiscal and per-ton abatement costs.[6] By contrast, policies that promote technological innovation may offer a pathway to reducing emissions while helping to rein in long-run energy costs.

> *For policymakers, the key takeaway is that while estimating the effects of emissions is difficult, the evidence supports the role of public R&D in driving clean-energy innovation.*

One such approach is public investment in energy research and development (R&D). By accelerating innovation, public R&D spending can reduce the costs of cleaner technologies, facilitate their integration into existing energy systems, and ultimately enable a cleaner, more affordable energy system. This paper evaluates the effectiveness of government R&D spending in stimulating clean energy innovation, as measured through patent activity, and its relationship to aggregate greenhouse gas emissions.

To do so, we analyze data from the International Energy Agency (IEA) on public spending on energy R&D across 23 countries from 2001 to 2020, covering a wide range of technologies, including renewable energy, nuclear fission and fusion, hydrogen and fuel cells, energy efficiency, and energy storage. We evaluate the relationship between this spending and IEA data on clean energy patents by country and, after controlling for macroeconomic and environmental policy variables, find that a 10 percent increase in public clean energy R&D is associated with a 0.8 to 1.2 percent increase in clean energy patents, after a five-year lag.

Importantly, this effect depends on the broader policy environment. When interacting R&D spending with an index of market-based environmental policies, such as carbon taxes, cap-and-trade systems, and other pollution pricing instruments, we find that stronger market-based policy environments amplify the impact of public R&D on innovation. In contrast, no similar effect is observed when interacting R&D with non-market-based policies, which include technology standards and mandated pollution limits.

We also evaluate the relationship between aggregate emissions and clean energy patenting, but do not find a robust effect. This absence of a consistent, measurable relationship likely reflects data limitations and confounding factors that obscure the short- to medium-term, emissions impacts of clean energy innovation, rather than evidence that it has no effect on emissions.

Overall, these results are consistent with existing research. There is a clear, consistent link between public R&D and clean energy innovation. Findings on the relationship between innovation and emissions are more mixed. For policymakers, the key takeaway is that while estimating the effects of emissions is difficult, the evidence supports the role of public R&D in driving clean-energy innovation. Given the knowledge spillovers from R&D, well-targeted government support can generate substantial social benefits.

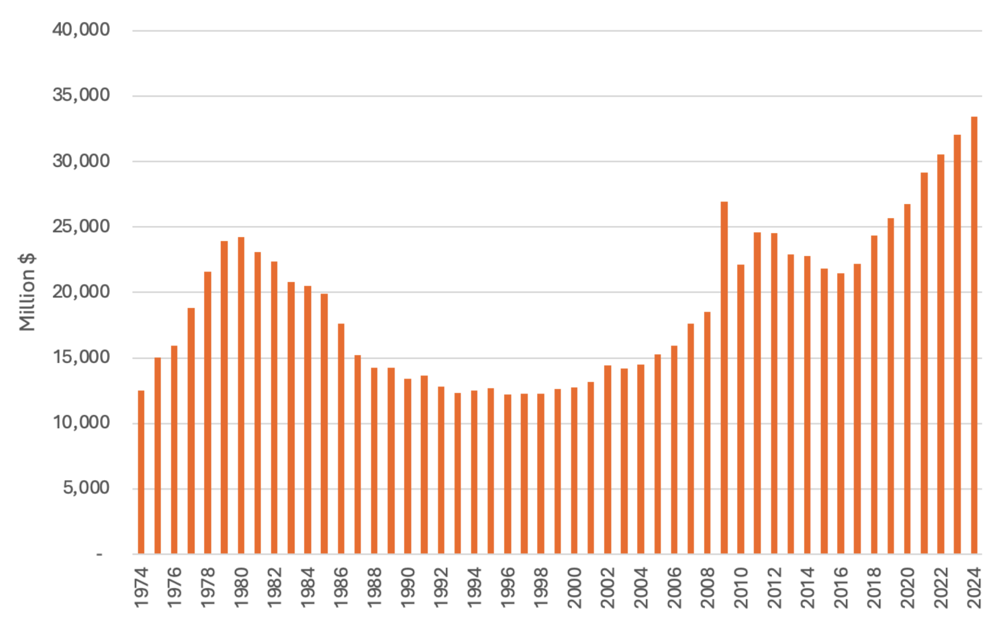
Background

Government spending on energy R&D peaked in the late 1970s and early 1980s, when energy crises prompted Western governments to explore alternative energy sources.[7] As these energy crises faded, funding declined sharply, reaching a low point in the 1990s. Since then, public R&D spending, both globally and in the United States, has gradually increased as mitigating the risks of climate change has become a dominant driver of the development of non-fossil-fuel energy technologies. Globally, clean energy R&D, or spending on renewable energy, nuclear fission and fusion, hydrogen and fuel cells, energy efficiency, and other power and storage technologies, reached a new peak, in real terms, in 2024.[8] In the United States, aside from a temporary surge created by the American Recovery and Reinvestment Act of 2009, federal clean-energy R&D in 2023 reached its highest level since the early 1980s. However, it remains well below the peaks of the 1970s, in both absolute terms and as a percentage of GDP.[9]

Figure 1.

Public Investment in Low-Carbon Innovation Peaked in 2024

Total IEA member government spending on low-carbon energy R&D, 1974–2024 (2024 USD, PPP)



Source: IEA.

In several areas, public support for clean energy R&D has played a clear role in making clean technologies cost competitive. Wind turbines, solar photovoltaics, and lithium-ion batteries have all experienced substantial cost declines over the past few decades, and economic research identifies public R&D support as an important contributor to these improvements and to the growing consumption of renewable energy.[10] Similarly, the U.S. shale gas revolution built on decades of public R&D that spurred innovation in advanced drilling and subsurface technologies, expanding the technical feasibility of shale extraction.[11] The subsequent surge in natural gas production has been a leading factor in decarbonizing the U.S. energy sector, and some evidence suggests it may have accelerated a transition to renewable energy sources.[12]

Critically, energy is an input for nearly all economic activity; therefore, clean energy is not the end-all be-all. Public support for its development is worthwhile only to the extent that it increases energy affordability, cost-effectively reduces pollution, or both. While heterogeneous customers may be willing to pay a premium for specific energy when available, broader willingness to pay for emissions reductions remains low. Energy innovation can accomplish both.

THE PROSPECTIVE BENEFITS OF CLEAN ENERGY

Energy technologies, resources, and energy policy have become highly politicized. Yet technologies such as wind and solar power, energy storage, hydrogen fuel cells, and nuclear power can offer dual benefits: improving long-term energy affordability and reducing greenhouse gas emissions. Because large-scale deployment of clean energy is relatively recent, direct empirical evaluation remains difficult. But early evidence suggests positive outcomes for both emissions and energy affordability.

Cost and Affordability Effects

The cost implications of clean energy technologies are difficult to disentangle. Though renewable energy sources and electric vehicles (EVs) have lower marginal operating costs, their high initial capital costs and system integration requirements can lead to additional expenses. This means that, when total lifetime and broader economy-wide costs (including subsidies) are considered, clean technologies may not be cost-competitive with fossil-fuel technologies.

EVs, for example, have higher upfront costs than ICE vehicles and may require charging infrastructure for first-time buyers. Their overall cost effectiveness for a private consumer depends on regional factors, including gasoline and electricity prices.[13] EVs' high initial cost has motivated federal and state governments to provide subsidies designed to make them cost-competitive with ICE vehicles as a tool to limit emissions. However, even setting aside questions about the true value of limiting emissions, the effectiveness of such subsidies depends critically on their design and local conditions, and existing evidence suggests that, at current and recent historical levels in the United States, EV subsidies have been costly and inefficient relative to their projected benefits.[14]

Continued technological progress for battery range and charting stations may reduce EV costs independently of climate-motivated subsidies, and a recent National Academies report projects that battery EVs could reach cost parity with gasoline vehicles by the end of this decade, based on declining battery costs, before accounting for purchase subsidies.[15]

Meanwhile, integrating variable renewable energy into existing power systems imposes system-wide costs that can offset their low operational expenses. Wind and solar frequently necessitate transmission expansion and backup capacity, requiring additional resources to ensure grid reliability and creating additional costs.[16] Additional R&D, especially in grid integration technologies and storage, will likely help reduce these costs and enable renewables to reach their full cost-saving potential.

Even with these challenges, the available evidence does find that renewable energy has been associated with modest reductions in wholesale electricity costs. Electricity systems operate through "merit-order dispatch," in which the marginal cost of the last generator needed to meet demand sets the market price.[17] Because wind and solar have near-zero marginal costs, they tend to lower wholesale prices when available.

Empirical studies confirm that renewable penetration has exerted downward pressure on wholesale prices, though these savings are small relative to the influence of other factors, such as natural gas price fluctuations in the United States.[18] Most renewable energy has been built in places with government support, such as production and investment tax credits in the United States, and the empirical evidence therefore reflects outcomes observed when renewable generation benefits from such subsidies. As a result, a full assessment of the overall cost benefits of renewable energy depends on both the extent to which renewables lower wholesale electricity prices and the economics of the public support used to deploy them. The available evidence focuses narrowly on electricity market outcomes, but it does illustrate how renewable generation can put downward pressure on wholesale prices once it is built and operating. Retail price structures and regulatory frameworks may further limit the extent to which these wholesale savings are ultimately passed on to consumers.

Taken together, the experiences of EVs and renewable electricity suggest that, although their cost competitiveness still depends on broader market conditions and system-level considerations, substantial progress has been made in reducing their costs to the point that they are increasingly viable, mainstream options.

Emissions Effects

The emissions benefits of zero and low-emissions energy technologies are theoretically straightforward but are practically nuanced. Increased renewable electricity generation should reduce fossil-fuel use and thus emissions. In practice, the variability and intermittency of wind and solar require backup generation, often from fossil-fuel plants. This can force fossil-fuel plants to operate inefficiently or require rapid ramping from higher-emitting units, partially offsetting emissions reductions.[19]

Similarly, the emissions effects of electric vehicles (EVs) depend on lifecycle considerations, including emissions from vehicle and battery manufacturing, as well as the carbon intensity of the electricity used for charging.[20] Energy-efficiency improvements, such as increasing fuel efficiency for cars or appliances that use less electricity, may also create rebound effects, where reduced operating costs lead to increased energy use.[21]

Nevertheless, academic research generally finds that zero-emissions energy technologies reduce emissions overall. Renewable electricity consumption reduces both total CO2 emissions and grid carbon intensity.[22] Battery EVs generate net emissions reductions relative to internal combustion engine (ICE) vehicles after roughly two years of use.[23] And research on energy efficiency finds that, even after accounting for the rebound effects, efficiency improvements reduce emissions.[24]

Taken together, the evidence on emissions and costs suggests that clean energy technologies may deliver both environmental benefits and, in some settings, improve energy affordability. The extent of these benefits likely depends on continued cost reductions and technological progress, potentially motivating continued government support for early-stage energy R&D.

THE ECONOMIC BENEFITS OF PUBLIC R&D SUPPORT

Historically, government support for clean energy technologies has often taken the form of direct deployment policies, such as tax credits, mandates, and other subsidies aimed at accelerating the adoption of relatively mature technologies. These policies are typically justified by their expected climate and environmental benefits, but they rely on contested economic assumptions and face political resistance, particularly among those skeptical of climate policy or concerned with the fiscal costs of large subsidies.[25] Importantly, however, these direct subsidies and forms of government support are distinct from policies that support R&D. Public investment in R&D targets an earlier stage of the innovation process and is motivated by a well-established economic rationale. As a result, public R&D support has an economic justification independent of any perceived climate or environmental benefits and has the potential to deliver more tangible outcomes, including long-run improvements in affordability and greater energy security. Hedging climate-related risks is an additional, but secondary, benefit of policies designed to spur clean energy innovation.

Government funding for R&D has long been recognized as a powerful tool for addressing a fundamental market failure. In his seminal 1962 paper, economist Kenneth Arrow argued that knowledge exhibits the characteristics of a public good and that, because firms cannot fully appropriate the benefits of the knowledge they generate, competitive markets will underinvest in R&D relative to the socially optimal level.[26] This is especially true when innovation is costly, risky, and easily imitated.

> *Well-designed R&D programs have consistently been shown to create sizable social returns by stimulating innovation, boosting productivity, and driving long-term economic growth.*

The policy implication of Arrow's insight is that governments can improve economic efficiency by publicly financing R&D. Public funding, especially for basic and pre-commercial scientific research, helps overcome risk, reduce the cost of early-stage invention, and support innovative activities that private firms would underprovide. The resulting discoveries diffuse throughout the economy, generating substantial positive spillovers. Well-designed R&D programs have consistently been shown to create sizable social returns by stimulating innovation, boosting productivity, and driving long-term economic growth.[27]

R&D subsidies do have risks. Public funding may crowd out, rather than complement, private investment, and government R&D spending can be steered toward politically attractive projects rather than those with the highest potential social value.[28] These concerns are especially relevant for technologies closer to commercial deployment. There is a compelling rationale for targeted programs to help early-stage technologies cross the "valley of death" between initial research and commercial deployment, a phase in which private financing is sometimes scarce and unwilling to take bets on first-of-a-kind technologies. Consequently, many promising innovations fail. However, excessive political influence can lead to misallocation of resources and pork-barrel spending; one infamous example in clean energy is the failure of solar firm Solyndra in 2011 after receiving substantial stimulus funding.[29] Members of Congress will procure taxpayer funding for projects in their respective districts regardless of the economic merit because the political rates of return can be higher. Therefore, the design and targeting of R&D programs are important factors in their success.[30]

Energy innovation potentially presents an even stronger case for government intervention.[31] In addition to the knowledge and economic spillovers, the risks of pollution and climate change create an additional market failure as firms do not face the full social costs of their emissions. The combination of these two externalities suggests that private firms will underinvest in clean technologies even more significantly than firms in other domains.[32] Economic theories of technological path dependence and directed technological change reinforce this concern. As fossil-fuel technologies continue to mature they become increasingly entrenched. Work by Nobel laureates Daron Acemoglu and Philippe Aghion and their coauthors shows that firms will tend to invest in incremental improvements in fossil-fuel technologies rather than riskier breakthroughs in clean energy alternatives.[33] This supports a need for strong ,sustained policies to support research into clean technology.

Empirical research confirms these theoretical insights by demonstrating that clean energy research creates substantial knowledge spillovers. A study using patent citation data, for example, documents that innovations in renewable energy technologies, especially solar and energy storage, produce significant knowledge flows not only within their own technological domains, but also to other energy technologies and into sectors outside of power generation.[34] A separate comparison of "clean" and "dirty" technologies shows that clean patents tend to generate higher levels of spillovers, including more citations and more influential citations, than fossil-fuel patents.[35] Together, this evidence underscores the economic rationale for targeted public R&D support for zero and low-emissions energy technologies.

THE LINK BETWEEN R&D, INNOVATION, AND EMISSIONS OUTCOMES

Beyond the broader spillovers and societal benefits of clean energy research, an important question is how effectively public R&D achieves its first-order goals of inducing innovation and ultimately reducing emissions. A range of evidence supports the existence of a relationship between R&D investment and innovative activity. However, the empirical support becomes more mixed when attention shifts from innovation itself to actual downstream emissions outcomes.

Much of the literature relies on patents as a proxy for innovation, but this metric has well-known limitations.[36] First, patent value is highly skewed. A small share of patents accounts for the bulk of economic and technological significance. Second, not all inventions are patented, meaning patent counts systematically understate innovative activity. In addition, strategic patenting behavior, institutional differences across countries, and delays between inventive activity and patent filings further complicate the interpretation of patent data. As a result, patents are a useful but imperfect indicator of innovation, and findings based on them should be interpreted cautiously.

With these limitations, empirical research typically finds a robust link between R&D spending, both public and private, and patenting activity.[37] This result generally holds up when examining the specific effects of government support for clean energy R&D, though there are important qualifications. A 2002 study by economist David Popp, for example, examined the relationship between energy prices and federal R&D on private energy-related patents while explicitly controlling for the existing stock and quality of technological knowledge (i.e., the cumulative body of ideas and past research that inventors can draw upon). Studying the period from 1970 to 1994, he finds that energy prices and the quality-adjusted stock of knowledge had strong, statistically significant positive effects on clean energy patents, whereas federal R&D expenditures had little to no direct effect. However, when accounting for changes in the orientation of federal energy R&D, particularly a shift towards more upstream, basic research after President Ronald Reagan took office in 1981, Popp finds government R&D plays a measurable, albeit modest, role in creating long-run knowledge accumulation. In other words, public support for basic R&D contributes indirectly to future clean energy innovation by expanding the knowledge base on which subsequent research builds. When this post-1981 shift is not accounted for, earlier periods of relatively ineffective applied R&D obscure this longer-run effect.[38]

A 2010 study by Nick Johnstone, Ivan Hašcic, and Popp analyzed the effects of environmental policies on renewable energy innovation as measured by patent applications to the European Patent Office.[39] Examining 25 countries from 1978 to 2003, they conclude that public R&D spending on renewable technologies is a significant determinant of patenting, though the effects vary by renewable technologies, with the largest effects for wind, solar, and geothermal, and insignificant results for ocean energy and biomass and waste technologies. Country-specific evidence from the United States, Canada, Germany, South Korea, and China likewise supports a positive relationship between government R&D spending and clean energy patenting.[40]

The connection between innovation and actual emissions is less clear. One study, for example, found that R&D spending is associated with lower average CO2 emissions in a sample of OECD and G7 countries in the long run. However, it concluded that the effect differed by period and country, with around 40 percent of OECD countries demonstrating no long-term negative effect.[41] A separate analysis finds that total private R&D is associated with a long-run reduction in greenhouse gas emissions conditional on the stringency of other environmental policies, particularly market-based instruments.[42] Without accounting for the interaction of such policies, private R&D had no meaningful relationship with emissions. Similarly, research examining public energy R&D finds improvements in energy efficiency, but no statistically significant relationship with carbon intensity, suggesting that government support for R&D by itself is not sufficient to deliver reductions in emissions per unit of economic output.[43]

Studies linking patent-based measures of innovation to emissions outcomes reach comparable conclusions. A recent review of the "eco-innovation" literature finds that green patents are often associated with lower emissions, but that the strength and consistency of this relationship depend on a wide range of factors and vary substantially across industries and countries.[44] Environmental regulations and complementary policies are important moderators of the emissions impacts of eco-innovation. In addition, other analysis finds that the emission-reducing effects of green patents are concentrated in higher-income countries.[45]

Taken together, the literature implies a consistent but often modest relationship between R&D and clean energy innovation. However, the extent to which this innovation translates into actual emissions reductions depends on the broader policy mix and institutional conditions.

THE ROLE OF PUBLIC R&D IN BROADER ENVIRONMENTAL POLICY

A traditional question in the literature on energy innovation asks whether policies that induce innovation on the supply side, known as "technology push", or policies that create a market need for innovative technologies, "demand pull", are more effective in stimulating innovation.[46] Technology-push policies, including government R&D, are justified based on the conception of innovation as a result of standard scientific progress. Invention progresses from basic research to applied and commercial developments, and the key role of government in this process is the support of this knowledge-building process. The demand-pull framework instead considers that innovation occurs as a response to some market need. Firms facing problems will invest in developing solutions, and in so doing will create innovative technologies.

In general, both mechanisms have been found to play a role. R&D investment can spur innovation, but without a market need for such technologies, there is little incentive for commercialization or deployment. This is especially relevant in the environmental context, where there is limited existing market demand for clean technologies unless they are cost-competitive with conventional energy sources. Both public and private R&D investments are necessary to create the building blocks of invention, while the extent to which those building blocks result in large-scale adoption and deployment of emissions-free energy depends on other mechanisms.

These mechanisms can take a variety of forms. Broadly speaking, there are market-based instruments, such as carbon taxes and cap-and-trade systems, and command-and-control regulations, including environmental performance standards and technology mandates. Historically, market-based mechanisms have been viewed by most economists as the most efficient tools for addressing environmental concerns and promoting innovation because they are flexible and reward firms for exceeding the government's explicit policy goals.[47] Non-market-based mechanisms, by contrast, tend to be more rigid and may respond poorly when innovation cannot keep pace with regulatory standards.

For example, while a market-based mechanism rewards emissions reductions regardless of the technology used, a technology mandate requires firms to adopt a specific technology, even if it proves ineffective or suboptimal. Furthermore, such regulations typically compel firms to innovate only up to the level required to meet the standard. Whereas carbon pricing incentivizes firms to reduce emissions to the fullest extent technologically possible, emissions standards require reductions only to the degree mandated by the government. There is, however, an important nuance in this debate: in certain cases, additional market failures or specific technological needs are argued to justify use of regulation and other non-market-based instruments.[48]

Market-based policies, in particular a carbon tax, are often argued to be the optimal climate and environmental policy tool in an ideal world. In practice, however, environmental policy operates through a complex mix of interventions, and interactions between multiple policy tools may create unintended adverse effects.[49] In particular, layering a carbon tax on top of an existing web of federal regulations, subsidies, and other non-market interventions undermines the effectiveness of carbon pricing and may impose cumulative burdens that exceed the perceived climate benefits of such a policy.[50] Moreover, assessments of environmental policy should account for government interventions that directly impede broader policy objectives, including permitting barriers and transmission constraints that delay or prevent the cost-effective adoption of new, clean energy technologies.[51]

These constraints help explain why innovation policy, especially public R&D subsidies, plays an important and distinct role within broader environmental policy. By lowering costs and expanding the set of feasible technologies, R&D support has the potential to deliver environmental and economic benefits with relatively little distortion. An extensive body of evidence affirms that, when considered in a broader environmental policy context, public R&D is shown to have positive effects on innovation.[52] At the same time, however, the actual effect on environmental outcomes, such as aggregate emissions, is less clear.[53] Given the identified importance of both technology-push and demand-pull policies in innovation and deployment of technologies that reduce emissions, this outcome is to be expected.

Analyzing the Role of R&D in Inducing Innovation and Reducing Emissions

The goal of this analysis is to provide a high-level assessment of whether public spending on clean energy R&D is helping to spur innovation and reduce greenhouse gas emissions. The analysis is intentionally limited in its scope and is not designed to produce a precise or definitive estimate of causal impacts. Instead, it offers an informed assessment based on publicly available international data. Strong conclusions would require more detailed data and more specialized analytical techniques.

With those limitations in mind, the findings suggest that public investment in clean energy R&D does play a meaningful role in promoting innovation, as measured by patent activity. However, the analysis does not find a clear empirical link between this innovation and reductions in emissions, a result that likely reflects the scope and limitations of the empirical approach, particularly the short time horizon and high level of aggregation, rather than the absence of a broader relationship. The core approach and key findings are described here. Additional technical details are provided in the appendix.

DATA SOURCES AND ANALYSIS FRAMEWORK

The analysis focuses on two main questions. First, does higher public spending on clean energy R&D lead to more clean energy innovation in later years? Second, does increased clean energy innovation translate into lower overall emissions over time? To answer these questions, we compare trends across countries and over time, while controlling for differences across countries and the effects of global shocks that affect all countries in a given year (e.g., economic cycles or energy price shocks).

We assemble a dataset covering 23 countries over the period 2000–2020. These countries are selected based on the availability of consistent data on public energy R&D spending, energy innovation, emissions, economic conditions, and environmental policy.

Data on clean energy patents and public energy R&D spending come from the International Energy Agency (IEA).[54] Patent counts reflect clean energy inventions and are assigned to countries based on the residence of inventors, with patents shared fractionally across countries when inventors are in more than one place. Public R&D spending is measured in inflation-adjusted 2024 prices and includes government funding for energy efficiency, renewable energy, nuclear fission and fusion, hydrogen and fuel cells, power and storage technologies, and other clean energy research areas. Spending related to fossil fuels and unallocated spending is excluded. Greenhouse gas emissions data are taken from the OECD and are measured in metric tons of CO2-equivalent, excluding emissions from land use, land-use change, and forestry (LULUCF).[55]

Basic economic controls, including GDP per capita and population, are from the World Bank.[56] To capture differences in environmental policy, we use the OECD's Environmental Policy Stringency (EPS) index, which summarizes the overall strength of a country's environmental regulations.[57] We also examine subindices for market-based and non-market-based policy stringency separately. To capture changes in domestic energy prices within countries, we include the energy component of the OECD Consumer Price Index as a proxy for energy price conditions, reflecting the role of energy costs in shaping incentives for clean energy innovation.[58]

Because patents and emissions outcomes do not respond immediately to funding or innovation, the analysis allows for time delays. Public R&D spending is compared to patenting outcomes five years later, reflecting the time needed for research funding to generate new inventions. Similarly, clean energy patenting is compared to emissions outcomes eight years later, reflecting additional time required for technologies to be adopted and deployed at scale. These time frames are based on the minimum periods for invention and commercialization in the energy sector found in existing research.[59] These, however, necessarily simplify a wide range of innovation and deployment timelines.[60]

To isolate the effects of public R&D from broader trends in innovation, we control for overall patenting activity unrelated to clean energy.[61] This helps ensure that observed relationships are not simply driven by general increases or decreases in innovation across the economy.

The analysis uses a panel regression framework that controls for country-specific characteristics that do not change over time, as well as for global year-specific effects that affect all countries simultaneously. We also examine whether the impact of public R&D differs with the strength and type of environmental policy in place by evaluating the interactions between R&D and environmental policy subindices.[62]

A key challenge in analyzing long-term trends in panel data is that many economic and environmental variables change gradually over time rather than fluctuating around a stable level. Public R&D spending, patenting activity, economic output, and emissions may all follow long-run upward or downward trends driven by structural forces such as economic growth, technological change, or long-term policy shifts. When such persistent trends are present, variables that share similar, but unrelated, trends may appear statistically related even when no meaningful relationship exists.

To assess this risk, we evaluate the properties of the data using a range of statistical diagnostics designed to detect persistent trends. The results of these tests are mixed, suggesting that long-run trends may be present for some variables.[63] To ensure that our findings are not driven solely by these potential long-term trends, we also evaluate models that focus on short-run, year-over-year changes in the variables of interest. By examining these short-run changes, we are able to investigate the relationship between public R&D, patenting, and emissions after removing long-term trends from the data.

RESULTS

The analysis finds evidence that higher public spending on clean energy R&D is associated with increased clean energy innovation five years later. However, it does not find a corresponding short- or long-term effect of innovation on aggregate greenhouse gas emissions, a result that likely reflects the scope and limitations of the analysis rather than the absence of longer-run or indirect effects.

Table 1.

Public Clean Energy R&D Spending Is Associated with an Increase in Later Patenting Activity

Elasticity of public R&D and patent activity

	Dependent variable:		
	ln(Clean energy patents)		
	Baseline	+ Econ & Policy	+ Non-Energy Patents & Price
ln(Public clean energy R&D) $_{t-5}$	0.068	0.082**	0.091***
Observations	341	341	341
R^2 (within)	0.019	0.052	0.064

Notes: All models include country and year fixed effects. The econ and policy column adds GDP per capita, population, and lagged environmental policy stringency. Non-energy patents and price column further includes lagged non-energy patent counts and lagged energy price index. Statistical significance is based on Driscoll–Kraay standard errors. Full results are reported in the appendix. *p<0.1; **p<0.05; ***p<0.01.

Public Clean Energy R&D and Innovation

Higher public spending on clean energy R&D is consistently associated with greater clean energy innovation, as measured by patent activity. As demonstrated in Table 1, after accounting for differences across countries, global economic shocks, macroeconomic conditions, and environmental policy stringency, we find that a 10 percent increase in clean energy R&D spending is associated with approximately a 0.8 percent increase in clean energy patenting five years later.[64]

This relationship is statistically significant and remains when controlling for broader innovation trends unrelated to energy and, as indicated in Table 2, when adjusting for potential long-run trends in the data by examining year-over-year changes rather than levels. The consistency of the results across these approaches suggests that it reflects a meaningful relationship, rather than a spurious result driven by long-term trends.

The effectiveness of R&D is not uniform across policy contexts. Our results, as reported in Table 3, show that market-based environmental policies amplify the impact of R&D on clean energy innovation.[65] As market-based environmental policy within a country becomes stronger, increases in public R&D spending translate into larger subsequent increases in patenting activity.[66] By contrast, we find no comparable amplification effect for non-market-based policies.

Table 2.

Similar Results for First-Difference Models Suggest That Estimated Elasticity Is Not the Result of Long-Term Trends

Elasticity of public R&D and patent activity

	Dependent variable:		
	Δln(Clean energy patents)		
	Baseline	+ Econ & Policy	+ Non-Energy Patents & Price
Δln(Public clean energy R&D)$_{t-5}$	0.106**	0.115**	0.117**
Observations	317	317	317
R^2 (within)	0.121	0.123	0.129

Notes: All models include country and year fixed effects. The econ and policy column adds GDP per capita, population, and lagged environmental policy stringency. Non-energy patents and price column further includes lagged non-energy patent counts and lagged energy price index. Statistical significance is based on Driscoll–Kraay standard errors. Full results are reported in the appendix. *p<0.1; **p<0.05; ***p<0.01.

Table 3.

Market-Based Policies Increase the Effectiveness of Public R&D

	Dependent variable:		
	ln(Clean energy patents)		
	Overall Policy	Market-based policy	Non-market-based policy
Δln(Public clean energy R&D)$_{t-5}$	0.091***	0.088***	0.072***
EPS index$_{t-5}$	-0.106**		
Market-based EPS index$_{t-5}$		-0.453***	
Δln(Public clean energy R&D)$_{t-5}$ x Market-based EPS index$_{t-5}$		0.073***	
Non-market-based EPS index$_{t-5}$			-0.008
Δln(Public clean energy R&D)$_{t-5}$ x Non-market-based EPS index$_{t-5}$			0.0004
Observations	341	341	341
R^2 (within)	0.064	0.082	0.051

Note: All models include country and year fixed effects, macroeconomic variables, and non-energy patent and energy price controls. Statistical significance is based on Driscoll–Kraay standard errors. Full results are reported in the appendix. *p<0.1; **p<0.05; ***p<0.01.

Innovation and Emissions Outcomes

In contrast to the clear relationship between public R&D and innovation, we do not find strong evidence that increased clean energy innovation is associated with lower aggregate greenhouse gas emissions.[67] Some specifications using long-run emissions levels suggest a statistically significant relationship. However, the data exhibit persistent long-term trends, raising concerns that these results may reflect shared underlying trends rather than a meaningful statistical association.[68] When we instead examine year-to-year changes, thereby reducing the influence of long-run movements, the relationship is no longer statistically detectable. For that reason, we do not view the emissions findings as robust.

This finding is consistent with much of the existing empirical literature and likely reflects the challenge of identifying emissions impacts using aggregate, country-level data. The absence of a measurable emissions effect is not evidence that clean energy innovation does not reduce emissions. Instead, it highlights the limits of what can be observed over relatively short time horizons and at broad levels of aggregation.

Discussion and Implications for Policymakers

These results point to several broader lessons about how innovation policy works in the energy sector and what it can realistically deliver.

First, the finding that public clean energy R&D spending is associated with increased innovation is consistent with a large body of prior research. Studies across a range of settings generally find that higher R&D investment leads to more patenting and inventive activity. While the estimated magnitude varies across studies, the effect identified here is within the range observed in previous clean-energy-specific analyses.[69]

Notably, the estimated elasticity in this analysis is on the lower end of what is often found in firm-level or industry-level studies of broader, non-energy-specific R&D and innovation.[70] This likely reflects the country-level scope of this analysis, which necessarily aggregates across technologies and sectors and may attenuate the measured effect. In addition, innovation in the energy sector tends to involve longer development timelines, higher capital intensity, and a more complex regulatory environment than innovation in many other industries.[71] These features may reduce the short-run responsiveness of patenting to increases in R&D funding.

From a policy perspective, the key takeaway is not the precise size of the elasticity we estimate, but its consistency and direction. Public clean energy R&D appears to do what is intended by spurring invention and expanding the stock of technical knowledge.

In contrast, the relationship between emissions and innovation is far less clear. This likely reflects structural features of the energy system rather than a failure of innovation policy. Emissions outcomes probably lag innovation by many years, longer than the lag built into this analysis.[72] While new inventions and patents may emerge relatively quickly following R&D funding, substantial emissions reductions depend on the widespread deployment of new technologies. Energy systems are dominated by long-lived assets, such as power plants, vehicles, and industrial equipment, that turn over slowly. Even when new technologies are available, it may take decades for them to materially affect emissions at an aggregate level.[73]

Aggregate emissions are also driven by powerful macroeconomic and structural forces that may overwhelm the marginal effect of innovation in the short to medium run.[74] Fuel prices, economic growth, population trends, energy demand, and business cycles all shape emissions trajectories.[75] At the country level, these forces may obscure the incremental impact of clean energy innovation, especially over a short period of time.

Finally, the emissions impact of innovation likely depends on complementary policies that encourage commercialization and deployment. The broad environmental policy measures used in this analysis may capture overall policy stringency, but they are coarse proxies for the specific regulatory and market instruments that directly influence technology adoption. Without distinguishing among technologies at different stages of maturity or accounting for deployment-specific policies, important nuances in how innovation translates into emissions outcomes may be missed.

Taken together, the absence of a consistent, statistically detectable relationship between innovation and emissions should not be interpreted as evidence that clean energy innovation has no effect on emissions. Rather, it highlights the difficulty of observing downstream impacts, such as on emissions or affordability, and underscores the importance of long-time horizons and the overall policy context when considering the benefits of energy innovation.

> *The overarching conclusion is that public clean energy R&D is an effective tool for stimulating innovation, but it is more effective when embedded within a broader policy framework.*

The overarching conclusion is that public clean energy R&D is an effective tool for stimulating innovation, but it is more effective when embedded within a broader policy framework. In particular, market-based policies, such as carbon taxes and cap-and-trade systems, help create demand for clean technologies and reward emissions reductions, thereby strengthening the innovative impact of R&D funding.

For policymakers, this implies that R&D funding should not be considered in isolation. Depending on the ultimate goals of such funding, its benefits are likely maximized when coordinated with other policies that facilitate deployment and commercialization. At the same time, the choice of complementary policies requires care. Rigid, non-market-based regulations may have limited effects on innovation and, in some cases, might risk slowing the development of cost-effective clean energy technologies by limiting flexibility or locking in specific technologies.

Conclusion

Public investment in clean energy research and development offers an opportunity to balance emissions reductions with energy affordability. As many clean technologies, including electric vehicles, energy storage, and renewable electricity generation, remain in relatively early stages of widespread deployment, empirical evidence linking innovation to aggregate outcomes such as emissions reductions and energy price declines is necessarily limited.

The results presented here indicate that public R&D support is consistently associated with increased clean energy innovation, demonstrating that such policies are achieving their first-order objective of stimulating invention. Across countries and over time, higher public spending on clean energy research is followed by a measurable increase in patenting activity. This suggests that government investment is contributing to the expansion of technical knowledge and the development of new energy technologies.

Many of today's mature clean technologies benefited from sustained public R&D support long before they approached cost competitiveness. Continued investment in early-stage research and breakthrough technologies offers the potential to further reduce costs, improve system integration, and expand the range of economically viable clean energy options. Over time, such progress can help lower the long-run costs of decarbonization and ease the tradeoff between environmental progress and energy abundance.

Public R&D is unlikely to serve as a standalone solution to improving energy affordability while addressing climate risks. However, it is an important component of a broader energy policy strategy. In the context of rising electricity demand and political resistance to high-cost regulatory interventions, sustained support for innovation remains one of the most economically grounded and durable policy tools available.

David Kemp is Research Fellow for Climate and Energy Policy at C3 Solutions.

Appendix Endnotes

1 EIA, "Per Capita Energy-Related CO2 Emissions Decreased in Every State between 2005 and 2023," Today in Energy, September 15, 2025, https://www.eia.gov/todayinenergy/detail.php?id=66104.

2 Brad Plumer, "U.S. Efforts to Cut Emissions Stalled in 2024 as Power Demand Surged," The New York Times, January 9, 2025, https://www.nytimes.com/2025/01/09/climate/us-emissions-solar-wind-power.html.

3 Jonathan Watts and Wajã Xipai, "'Change Course Now': Humanity Has Missed 1.5C Climate Target, Says UN Head," The Guardian, October 27, 2025, https://www.theguardian.com/environment/2025/oct/28/change-course-now-humanity-has-missed-15c-climate-target-says-un-head.

4 David Kemp, "Energy Price Honesty," C3 News Magazine, October 14, 2025, https://c3newsmag.com/energy-price-honesty/; and Nick Loris, "The Left's Energy Amnesia," C3 News Magazine, October 8, 2025, https://c3newsmag.com/the-lefts-energy-amnesia/.

5 Ryan Wiser et al., "Factors Influencing Recent Trends in Retail Electricity Prices in the United States," The Electricity Journal 38, no. 4 (December 2025): 1–10, https://doi.org/10.1016/j.tej.2025.107516; IEA, "World Energy Outlook 2025, November 12, 2025, https://www.iea.org/reports/world-energy-outlook-2025.

6 Devin Hartman, "The Inflation Reduction Act's Energy Provisions Require Reform to Benefit Society," C3 News Magazine, May 13, 2025, https://c3newsmag.com/the-inflation-reduction-acts-energy-provisions-require-reform-to-benefit-society/.

7 Corrie E. Clark, "Renewable Energy R&D Funding History: A Comparison with Funding for Nuclear Energy, Fossil Energy, Energy Efficiency, and Electric Systems R&D," Congressional Research Service no. RS22858, June 18, 2018, https://www.congress.gov/crs-product/RS22858.

8 IEA, "Energy Technology RD&D Budgets Data Explorer," https://www.iea.org/data-and-statistics/data-tools/energy-technology-rdd-budgets-data-explorer.

9 Kelly Sims Gallagher and Laura Diaz Anadon, "DOE Budget Authority for Energy Research, Development, and Demonstration Database," Fletcher School of Law and Diplomacy, Tufts University; Department of Land Economy, Center for Environment, Energy and Natural Resource Governance (C-EENRG), University of Cambridge; and Belfer Center for Science and International Affairs, Harvard Kennedy School, July 8, 2020, https://www.belfercenter.org/publication/database-us-department-energy-doe-budgets-energy-research-development-demonstration-1; and Eric G. O'Rear et al., "Quantifying Federal Investments in Advancing Energy Innovation," Rhodium Group, March 26, 2025, https://rhg.com/research/federal-investments-in-energy-innovation/.

10 Goksin Kavlak, James McNerney, and Jessika E. Trancik, "Evaluating the Causes of Cost Reduction in Photovoltaic Modules," Energy Policy 123 (2018): 700–710, https://www.sciencedirect.com/science/article/abs/pii/S0301421518305196; Yi Zhou and Alun Gu, "Learning Curve Analysis of Wind Power and Photovoltaics Technology in US: Cost Reduction and the Importance of Research, Development and Demonstration," Sustainability 11 (2019): 2310, http://dx.doi.org/10.3390/su11082310; Mark Bolinger, Ryan Wiser, and Eric O'Shaughnessy, "Levelized Cost-Based Learning Analyisis of Utility Scale Wind and Solar in the United States," iScience 25, no. 6 (2022): 104378, https://doi.org/10.1016/j.isci.2022.104378; Micah S. Ziegler, Juhyun Song, and Jessikea E. Trancik, "Determinants of Lithium-Ion Battery Technology Cost Decline," Energy & Environmental Science 14 (2021): 6074, https://doi.org/10.1039/D1EE01313K; and Dierk Herzer, "The Impact of Government-Funded Renewable Energy R&D on Its Consumption," Journal of Policy Modeling 47, no. 5 (2025): 903–918.

11 The Breakthrough Institute, "US Government Role in Shale Gas Fracking History: A Response to Our Critics," March 1, 2012, https://thebreakthrough.org/issues/energy/us-government-role-in-shale-gas-fracking-history-a-response-to-our-critics.

12 David Lindequits and Samuel Selent, "Did Shale Gas Green the U.S. Economy?" Energy Economic 145 (May 2025): 108388, https://doi.org/10.1016/j.eneco.2025.108388.

13 David Rapson and Erich Muehlegger, "The Economics of Electric Vehicles," Review of Environmental Economics and Policy 17, no. 2 (2023), https://doi.org/10.1086/725484.

14 See, for example, Philip Rossetti and David Kemp, "The Case for Repealing IRA Clean Energy Subsidies," R Street Institute, May 19, 2025, https://www.rstreet.org/?post_type=commentary&p=87394; Hunt Allcott et al., "The Effects of ``Buy American": Electric Vehicles and the Inflation Reduction Act," NBER Working Paper No. 33032, December 2024; David S. Rapson and Erich Muehlegger, "The Economics of Electric Vehicles," Review of Environmental Economics and Policy 17, no. 2 (2023): 274–94, https://doi.org/10.1086/725484; Stephen P. Holland et al., "Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors," American Economic Review 106, no. 12 (2016): 3700–3729, https://doi.org/10.1257/aer.20150897.

15 National Academies of Sciences, Engineering, and Medicine, Assessment of Technologies for Improving Light-Duty Vehicle Fuel Economy—2025–2035 (Washington, DC: The National Academies Press, 2021), https://doi.org/10.17226/3154.

16 Emmanuel Ejuh Che et al., “The Impact of Integrating Variable Renewable Energy Sources into Grid-Connected Power Systems: Challenges, Mitigation Strategies, and Prospects,” Energies 18 (2025): 689, https://doi.org/10.3390/en18030689; and M. Bala Prasad et al., “Renewable Energy Integration in Modern Power Systems: Challenges and Opportunities,” E3S Web of Conferences 591 (2024): 03002, https://doi.org/10.1051/e3sconf/202459103002.

17 Klaas Würzburg, Xavier Labandeira, and Pedro Linares. “Renewable Generation and Electricity Prices: Taking Stock and New Evidence for Germany and Austria.” Energy Economics, Supplement Issue: Fifth Atlantic Workshop in Energy and Environmental Economics, vol. 40 (December 2013): S159–71. https://doi.org/10.1016/j.eneco.2013.09.011.

18 Andrew Mills, Ryan Wiser, Dev Millstein, et al. “The Impact of Wind, Solar, and Other Factors on the Decline in Wholesale Power Prices in the United States.” Applied Energy 283 (February 2021): 116266. https://doi.org/10.1016/j.apenergy.2020.116266; Lion Hirth. “What Caused the Drop in European Electricity Prices? A Factor Decomposition Analysis.” The Energy Journal 39, no. 1 (2018): 143–58, https://doi.org/10.5547/01956574.39.1.lhir; and Zsuzsanna Csereklyei, Songze Qu, and Tihomir Ancev. “The Effect of Wind and Solar Power Generation on Wholesale Electricity Prices in Australia.” Energy Policy 131 (August 2019): 358–69, https://doi.org/10.1016/j.enpol.2019.04.007.

19 Dhruv Suri, Jacques de Chalendar, and Inês M L Azevedo, “Assessing the real implications for CO2 as Generation from Renewables Increases,” Nature Communications 16, no. 1 (2025): 7124, https://doi.org/10.1038/s41467-025-59800-4; and David Kemp, “EPA’s New Power Plant Emissions Rule Relies on Optimistic Assumptions about Our Energy Future,” Cato at Liberty, May 22, 2024, https://www.cato.org/blog/epas-new-power-plant-emissions-rule-relies-optimistic-assumptions-about-our-energy-future.

20 Georg Bieker, “A Global Comparison of the Life-Cycle Greenhouse Gas Emissions of Combustion Engine and Electric Passenger Cars,” International Council on Clean Transportation White Paper, 2021, https://theicct.org/sites/default/files/publications/Global-LCA-passenger-cars-jul2021_0.pdf.

21 Nick Hanley et al., “Do Increases in Energy Efficiency Improve Environmental Quality and Sustainability?” Ecological Economics 68, no. 3 (2009): 692–709, https://doi.org/10.1016/j.ecolecon.2008.06.004; and Christoph Bohringer and Nicholas Rivers, “The Energy Efficiency Rebound Effect in General Equilibrium,” Journal of Environmental Economics and Management 109 (2021), https://doi.org/10.1016/j.jeem.2021.102508.

22 See, for example, Maxwell Kongkuah and Noha Alessa, “Renewable Energy and Carbon Intensity: Global Evidence from 184 Countries (2000–2020),” Energies 18, no. 13 (2025): 3236, https://doi.org/10.3390/en18133236; Fakhri Hasanov et al., “Theoretical Framework for the Carbon Emissions Effects of Technological Progress and Renewable Energy Consumption,” Sustainable Development 29, no 5 (2021): 810–822, https://doi.org/10.1002/sd.2175; and Yongming Huang, Zebo Kuldasheva, and Raufhon Salahodjaev, “Renewable Energy and CO2 Emissions: Empirical Evidence from Major Energy-Consuming Countries,” Energies 14 (2021): 7504, https://doi.org/10.3390/en14227504.

23 Pankaj Sadavarte, Drew Shindell, and Daniel Loughlin, “Comparing the Climate and Air Pollution Footprints of Lithium-Ion BEVs And ICEs in the US Incorporating Systemic Energy System Responses,” PLOS Climate 4, no. 10 (2025), https://doi.org/10.1371/journal.pclm.0000714.

24 Bamadev Mahapatra and Mohd Irfan, “Asymmetric Impacts of Energy Efficiency on Carbon Emissions: A Comparative Analysis between Developed and Developing Economies,” Energy 227, no. 15 (2021): 120485, https://doi.org/10.1016/j.energy.2021.120485; Saffet Akdag and Hakan Yıldırım, “Toward a Sustainable Mitigation Approach of Energy Efficiency to Greenhouse Gas Emissions in the European Countries,” Heliyon 6, (2020), https://doi.org/10.1016/j.heliyon.2020.e03396; and Falik Bilgili et al, “Are Research and Development on Energy Efficiency and Energy Sources Effective in the Level of CO2 Emissions? Fresh Evidence from EU Data,” Development and Sustainability 26 (2024): 24183–24219, https://doi.org/10.1007/s10668-023-03641-y.

25 The relative benefits of these policies depend on uncertain estimates of the benefits of greenhouse gas reductions, and existing evidence suggests that the fiscal costs of many such subsidies often exceed what can be justified by mainstream estimates of their climate benefits. See, for example, David Kemp and Peter Van Doren, “How Should We Value the Future?” Regulation 48, no. 4 (2025), https://www.cato.org/regulation/winter-2025-2026/how-should-we-value-future; Philip Rossetti and David Kemp, “The Case for Repealing IRA Clean Energy Subsidies,” R Street Institute, May 19, 2025, https://www.rstreet.org/?post_type=commentary&p=87394.

26 K. J. Arrow. “Economic Welfare and the Allocation of Resources for Invention,” in Readings in Industrial Economics, edited by Charles K. Rowley (Macmillan Education UK, 1972), https://doi.org/10.1007/978-1-349-15486-9_13.

27 Zvi Griliches, “The Search for R&D Spillovers,” in R&D and Productivity: The Econometric Evidence (University of Chicago Press, 1998), https://www.nber.org/books-and-chapters/rd-and-productivity-econometric-evidence/search-rd-spillovers; Nicholas Bloom et al., “Identifying Technology Spillovers and Product Market Rivalry,” Econometrica 81 (2013): 1347–1393, https://doi.org/10.3982/ECTA9466; Charles I. Jones and John C. Williams, “Measuring the Social Return to R&D,” The Quarterly Journal of Economics 113, no. 4 (1998): 1119–1135, https://doi.org/10.1162/003355398555856.

28 Bettina Becker, “Public R&D Policies and Private R&D Investment: A Survey of the Empirical Evidence,” Journal of Economic Surveys 29, no. 5 (2015): 917–42, https://doi.org/10.1111/joes.12074.

29 David Rotman, “Solyndra: We Told You So,” MIT Technology Review, September 15, 2011, https://www.technologyreview.com/2011/09/15/191285/solyndra-we-told-you-so/; Gregory F. Nemet et al., “The Valley of Death, the Technology Pork Barrel, and Public Support for Large Demonstration Projects,” Energy Policy 119 (August 2018): 154–67, https://doi.org/10.1016/j.enpol.2018.04.008.

30 Linda R. Cohen et al., The Technology Pork Barrel (Brookings Institution Press, 1991).

31 Kenneth J. Arrow et al., “A Statement on the Appropriate Role for Research and Development in Climate Policy,” The Economists’ Voice 6, no. 1 (2009), https://doi.org/10.2202/1553-3832.1518.

32 Adam B. Jaffe et al., “A Tale of Two Market Failures: Technology and Environmental Policy,” Ecological Economics 54, nos. 2–3 (2005): 164–74, https://doi.org/10.1016/j.ecolecon.2004.12.027.

33 Daron Acemoglu et al., “The Environment and Directed Technical Change,” American Economic Review 102, no. 1 (2012): 131–66, https://doi.org/10.1257/aer.102.1.131; Philippe Aghion et al., “Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry,” Journal of Political Economy 124, no. 1 (2016): 1–51, https://doi.org/10.1086/684581; Daron Acemoglu et al., “Green Innovation and the Transition Toward a Clean Economy,” SSRN Electronic Journal, 2024, https://doi.org/10.2139/ssrn.4816734; Daron Acemoglu et al., Climate Change, Directed Innovation, and Energy Transition: The Long-Run Consequences of the Shale Gas Revolution, 2023, https://ssrn.com/abstract=4567661.

34 Joëlle Noailly and Victoria Shestalova, “Knowledge Spillovers from Renewable Energy Technologies: Lessons from Patent Citations,” Environmental Innovation and Societal Transitions 22 (March 2017): 1–14, https://doi.org/10.1016/j.eist.2016.07.004.

35 Antoine Dechezlepretre et al., “Knowledge Spillovers from Clean and Dirty Technologies,” GRI Working Papers no. 135, October 2017, https://ideas.repec.org//p/lsg/lsgwps/wp135.html.

36 For a summary of these limitations see Sadao Nagaoka et al., “Patent Statistics as an Innovation Indicator,” in Handbook of the Economics of Innovation, ed. Bronwyn H. Hall and Nathan Rosenberg, vol. 2 (North-Holland, 2010), https://doi.org/10.1016/S0169-7218(10)02009-5.

37 For a review of literature on private and social returns to R&D, see Bronwyn H. Hall et al., “Measuring the Returns to R&D,” in Handbook of the Economics of Innovation, ed. Bronwyn H. Hall and Nathan Rosenberg, vol. 2 (Elsevier, 2010), https://doi.org/10.1016/S0169-7218(10)02008-3.

38 Popp further clarifies these results in subsequent research: David Popp, “They Don’t Invent Them Like They Used to: An Examination of Energy Patent Citations Over Time,” Economics of Innovation and New Technology 15, no. 8 (2006): 753–76, https://doi.org/10.1080/10438590500510459.

39 Nick Johnstone et al., “Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts,” Environmental and Resource Economics 45, no. 1 (2010): 133–55, https://doi.org/10.1007/s10640-009-9309-1.

40 Josef Plank and C. Doblinger, “The Firm-Level Innovation Impact of Public R&D Funding: Evidence from the German Renewable Energy Sector,” Energy Policy 113 (February 2018): 430–38, https://doi.org/10.1016/j.enpol.2017.11.031; Dilvin Taşkın et al., “How Are Energy-Related R&D Investments Effective on Environment-Related Patents? Empirical Evidence from the USA and Canada,” Journal of Sustainable Development Issues, December 20, 2024, https://doi.org/10.62433/josdi.v2i2.36; Bongsuk Sung, “Do Government Subsidies Promote Firm-Level Innovation? Evidence from the Korean Renewable Energy Technology Industry,” Energy Policy 132 (September 2019): 1333–44, https://doi.org/10.1016/j.enpol.2019.03.009; Yu Bai et al., “The Impacts of Government R&D Subsidies on Green Innovation: Evidence from Chinese Energy-Intensive Firms,” Journal of Cleaner Production 233 (October 2019): 819–29, https://doi.org/10.1016/j.jclepro.2019.06.107.

41 Predrag Petrović and Mikhail M. Lobanov, “The Impact of R&D Expenditures on CO2 Emissions: Evidence from Sixteen OECD Countries,” Journal of Cleaner Production 248 (March 2020): 119187, https://doi.org/10.1016/j.jclepro.2019.119187.

42 Dierk Herzer, “Private R&D, Environmental Policy, and Greenhouse Gas Emissions,” 2025, https://www.tandfonline.com/doi/full/10.1080/10438599.2024.2328536.

43 Paola Garrone and Luca Grilli, “Is There a Relationship Between Public Expenditures in Energy R&D and Carbon Emissions Per GDP? An Empirical Investigation,” Energy Policy 38, no. 10 (2010): 5600–5613, https://doi.org/10.1016/j.enpol.2010.04.057.

44 Duarte-Kzam Samuel et al., “Conducting a Systematic Literature Review of Environmental Emissions Performance and Eco-Innovation Research,” International Journal of Innovation Studies, ahead of print, November 14, 2025, https://doi.org/10.1016/j.ijis.2025.10.005.

45 Kerui Du et al., “Do Green Technology Innovations Contribute to Carbon Dioxide Emission Reduction? Empirical Evidence from Patent Data,” Technological Forecasting and Social Change 146 (September 2019): 297–303, https://doi.org/10.1016/j.techfore.2019.06.010.

46 For a review of the evidence on the relative contributions of technology-push and demand-pull factors, see Joelle Noailly, “Directing Innovation Towards a Low-Carbon Future,” SSRN Electronic Journal, 2023, https://doi.org/10.2139/ssrn.4418873.

47 Energy prices have been shown to be an important indicator of energy innovation. See Philippe Aghion et al., “Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry,” Journal of Political Economy 124, no. 1 (2016): 1–51, https://doi.org/10.1086/684581; Raphael Calel and Antoine Dechezleprêtre, “Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market,” The Review of Economics and Statistics 98, no. 1 (2016): 173–91, https://doi.org/10.1162/REST_a_00470; David Popp, “Induced Innovation and Energy Prices,” American Economic Review 92, no. 1 (2002): 160–80, https://doi.org/10.1257/000282802760015658; Michael Grubb et al., “Induced Innovation in Energy Technologies and Systems: A Review of Evidence and Potential Implications for CO2 Mitigation,” Environmental Research Letters 16 (March 2021), https://doi.org/10.1088/1748-9326/abde07.

48 For a discussion of this nuance see David Popp, “Environmental Policy and Innovation: A Decade of Research,” NBER Working Paper No. 25631, March 2019, http://www.nber.org/papers/w25631.

49 Lawrence H. Goulder and Ian W. H. Parry, “Instrument Choice in Environmental Policy,” Review of Environmental Economics and Policy 2, no. 2 (2008): 152–74, https://doi.org/10.1093/reep/ren005.

50 Nick Loris et al., “A Comprehensive Analysis of Federal Greenhouse Gas Regulations and Subsidies,” C3 Solutions, August 2025, https://c3solutions.org/policy-paper/a-comprehensive-analysis-of-federal-greenhouse-gas-regulations-and-subsidies/.

51 Ian Banks and Nick Loris, “Options for Permitting and Regulatory Reform in the 119th Congress,” C3 Solutions, December 10, 2025, https://c3solutions.org/policy-paper/options-for-permitting-and-regulatory-reform-in-the-119th-congress/.

52 See, for example, Antoine Dechezleprêtre and Matthieu Glachant, “Does Foreign Environmental Policy Influence Domestic Innovation? Evidence from the Wind Industry,” Environmental & Resource Economics 58, no. 3 (2014): 391–413; Klaus Gugler et al., “Environmental Policies and Directed Technological Change,” Journal of Environmental Economics and Management 124 (March 2024): 102916, https://doi.org/10.1016/j.jeem.2023.102916; Nick Johnstone et al., “Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts,” Environmental and Resource Economics 45, no. 1 (2010): 133–55, https://doi.org/10.1007/s10640-009-9309-1; Michael Peters et al., “The Impact of Technology-Push and Demand-Pull Policies on Technical Change – Does the Locus of Policies Matter?,” Research Policy 41, no. 8 (2012): 1296–308, https://doi.org/10.1016/j.respol.2012.02.004; Elena Verdolini and Marzio Galeotti, “At Home and Abroad: An Empirical Analysis of Innovation and Diffusion in Energy Technologies,” Journal of Environmental Economics and Management 61, no. 2 (2011): 119–34, https://doi.org/10.1016/j.jeem.2010.08.004. One exception is Nesta et al., which finds no effect of public R&D on green patents. Lionel Nesta et al., “Environmental Policies, Competition and Innovation in Renewable Energy,” Journal of Environmental Economics and Management 67, no. 3 (2014): 396–411, https://doi.org/10.1016/j.jeem.2014.01.001.

53 Carolyn Fischer and Richard G. Newell, “Environmental and Technology Policies for Climate Mitigation,” Journal of Environmental Economics and Management 55, no. 2 (2008): 142–62, https://doi.org/10.1016/j.jeem.2007.11.001; Leonie P. Meissner et al., “It’s Not a Sprint, It’s a Marathon: Reviewing Governmental R&D Support for Environmental Innovation,” Journal of Environmental Planning and Management 69, no. 1 (2026): 1–27, https://doi.org/10.1080/09640568.2024.2359442; David Popp, “R&D Subsidies and Climate Policy: Is There a ‘Free Lunch’?,” Climatic Change 77, no. 3 (2006): 311–41, https://doi.org/10.1007/s10584-006-9056-z.

54 Patent data is from: IEA, “Energy Technology Patents Data,” https://www.iea.org/data-and-statistics/data-tools/energy-technology-patents-data-explorer. Energy R&D data is from: IEA, “Energy Technology RD&D Budgets,” https://www.iea.org/data-and-statistics/data-product/energy-technology-rd-and-d-budget-database-2.

55 OECD, “Air Emissions - Greenhouse Gas Emissions Inventories,” https://data-explorer.oecd.org/.

56 World Bank, “GDP per capita, PPP (constant 2021 international $)”, https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.KD; updated to 2024 prices using US deflator from World Bank, “GDP deflator: linked series (base year varies by country)”, https://data.worldbank.org/indicator/NY.GDP.DEFL.ZS.AD. Population data from World Bank, “Population, total,” https://data.worldbank.org/indicator/SP.POP.TOTL.

57 We demean the policy stringency variables to help with interpretation of interaction between R&D and policy stringency. The results are consistent when these variables are not centered. OECD, “OECD Environmental Policy Stringency Index,” https://data-explorer.oecd.org/. EPS index is described in Tobias Kruse et al., “Measuring Environmental Policy Stringency in OECD Countries: An Update of the OECD Composite EPS Indicator,” OECD Economics Department Working Papers, ahead of print, OECD Publishing, March 14, 2022, https://doi.org/10.1787/90ab82e8-en.

58 We use annual except for Australia, for annual data are not available. For Australia, we therefore use quarterly observations and calculate annual averages. OECD, Main Economic Indicators Database, Consumer Price Index: OECD Groups: Energy (Fuel, Electricity, and Gasoline, 2015 = 100).

59 Robert Gross et al., “How Long Does Innovation and Commercialisation in the Energy Sectors Take? Historical Case Studies of the Timescale from Invention to Widespread Commercialisation in Energy Supply and End Use Technology,” Energy Policy 123 (December 2018): 682–99, https://doi.org/10.1016/j.enpol.2018.08.061.

60 For example, David Popp uses an alternative measure of innovation, publication output, and finds a lag between government R&D funding and publication up to ten years. David Popp, Using Scientific Publications to Evaluate Government R&D Spending: The Case of Energy, no. w21415 (National Bureau of Economic Research, 2015), w21415, https://doi.org/10.3386/w21415.

61 We construct a variable measuring non-energy patent applications for IP5 family patent data, which cover patent applications at the five largest global patent offices. Clean energy and greenhouse-gas related patents are excluded from total patent data taken from OECD, “Patents by Technology,” https://data-explorer.oecd.org/.

62 Dierk Herzer reports that private R&D is associated with lower greenhouse gas emissions when interacted with market-based environmental policy stringency. See Dierk Herzer, “Private R&D, Environmental Policy, and Greenhouse Gas Emissions,” 2025, https://www.tandfonline.com/doi/full/10.1080/10438599.2024.2328536.

63 We conduct three unit root tests commonly used to assess whether panel data exhibit persistent long-term trends. These tests differ in how they aggregate information across countries and whether they explicitly account for cross-country dependence. For many variables, two of the tests often reject the presence of a unit root, while a test that explicitly accounts for cross-country dependence (Pesaran 2007), frequently fails to reject the unit root. Given this pattern, we cannot conclusively rule out the presence of persistent long-term trends. We therefore complement the analysis with models estimated in first differences. Full test results are reported in the appendix. M. Hashem Pesaran, “A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence,” Journal of Applied Econometrics 22, no. 2 (2007): 265–312, https://doi.org/10.1002/jae.951; G. S. Maddala and Shaowen Wu, “A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test,” Oxford Bulletin of Economics and Statistics 61, no. S1 (1999): 631–52, https://doi.org/10.1111/1468-0084.0610s1631; Kyung So Im et al., “Testing for Unit Roots in Heterogeneous Panels,” Journal of Econometrics 115, no. 1 (2003): 53–74, https://doi.org/10.1016/S0304-4076(03)00092-7.

64 The results reported here use Driscoll–Kraay standard errors. As shown in the appendix, diagnostic tests indicate substantial serial correlation in the regression residuals and evidence of cross-country dependence in several specifications. These aspects can lead conventional standard errors to understate uncertainty, motivating the use of robust inference methods.

65 The coefficients on the EPS index and subindices require careful interpretation. The EPS measures are demeaned, meaning they capture changes in policy stringency within a country over time, rather than differences in policy levels across countries. A negative coefficient does not necessarily mean that environmental policy reduces innovation overall. Instead, it may indicate that when a country’s environmental policy becomes more stringent than its usual level, clean energy patenting tends to be lower several years later. By contrast, when policy stringency is measured in absolute terms and country-specific effects are not controlled for, the estimated relationship is positive. Taken together, these results suggest that while stronger environmental policy is linked to higher innovation across countries, policy changes within a country may involve short-term adjustments or transitions that may slow patenting activity. Furthermore, in models that include interaction with public R&D, the standalone policy coefficients reflect the effect of policy stringency when public R&D is zero. The coefficient of interest in these models is the interaction effect, which show how policy and R&D jointly influence innovation.

66 The amplification effect disappears in year-over-year specifications, suggesting it reflects longer-run policy dynamics rather than short-run interactions.

67 Full results are reported in the appendix.

68 As reported in the appendix, panel unit root tests indicate that logged public clean energy R&D spending and logged clean energy patents are stationary in levels. By contrast, aggregate emissions do not consistently reject the presence of a unit root under the Pesaran (2007) test, which accounts for cross-sectional dependence. The strong long-term trend in emissions suggests the levels result may be driven by those trends rather than a reliable relationship.

69 Johnstone, Haščič, and Popp estimate a negative binomial model with a log link, such that the expected number of patent applications enters the regression in logarithmic form while public R&D expenditures enter in levels. We convert their coefficient estimates on public R&D (R&D, reported in their Table 5) into elasticities evaluated at the sample mean by multiplying each coefficient by the corresponding mean level of R&D expenditure (R&D, reported in their Table 4): R&D=R&DR&D. This implies an elasticity of roughly 0.04 for renewable energy patenting overall, and technology-specific elasticities of approximately 0.11 for wind, 0.09 for solar, and 0.04 for geothermal. Nick Johnstone et al., “Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts,” Environmental and Resource Economics 45, no. 1 (2010): 133–55, https://doi.org/10.1007/s10640-009-9309-1. And see estimates with similar magnitude in Klaus Gugler et al., “Environmental Policies and Directed Technological Change,” Journal of Environmental Economics and Management 124 (March 2024): 102916, https://doi.org/10.1016/j.jeem.2023.102916.

70 Jerry Hausman et al., “Econometric Models for Count Data with an Application to the Patents-R & D Relationship,” Econometrica 52, no. 4 (1984): 909–38, https://doi.org/10.2307/1911191; Bronwyn H. Hall et al., “Patents and R and D: Is There a Lag?” International Economic Review 27, no. 2 (1986): 265, https://doi.org/10.2307/2526504; Jérôme Danguy et al., “The R&D-Patent Relationship: An Industry Perspective,” European Investment Bank Papers 14, no. 1 (2009): 170–95.

71 David Popp et al., “Innovation and Entrepreneurship in the Energy Sector,” NBER Working Paper No. 27145, May 2020.

72 Robert Gross et al., “How Long Does Innovation and Commercialisation in the Energy Sectors Take? Historical Case Studies of the Timescale from Invention to Widespread Commercialisation in Energy Supply and End Use Technology,” Energy Policy 123 (December 2018): 682–99, https://doi.org/10.1016/j.enpol.2018.08.061.

73 Just deploying renewable generation, for example, may face long-time horizons. And deployment does not immediately translate into emissions reductions. Manuel A. Zambrano-Monserrate et al., “Dynamic Effects on Modern Renewable Energy Generation: The Role of Patents in Clean Energy Technology,” Energy 311 (December 2024): 133340, https://doi.org/10.1016/j.energy.2024.133340.

74 Ian Sue Wing, “Explaining the Declining Energy Intensity of the U.S. Economy,” Resource and Energy Economics 30, no. 1 (2008): 21–49, https://doi.org/10.1016/j.reseneeco.2007.03.001.

75 See, for example, Cosimo Magazzino et al., “The Impact of Energy Prices and Socio-Economic Factors on CO2 Emissions in OECD Countries: A STIRPAT and Machine Learning Analysis,” Energy Strategy Reviews 62 (November 2025): 101920, https://doi.org/10.1016/j.esr.2025.101920; María A. González-Álvarez and Antonio Montañés, “CO2 Emissions, Energy Consumption, and Economic Growth: Determining the Stability of the 3E Relationship,” Economic Modelling 121 (April 2023): 106195, https://doi.org/10.1016/j.econmod.2023.106195; Katarzyna Szymczyk et al., “The Effect of Energy Usage, Economic Growth, and Financial Development on CO2 Emission Management: An Analysis of OECD Countries with a High Environmental Performance Index,” Energies 14, no. 15 (2021), https://doi.org/10.3390/en14154671.

Appendices & Data

Appendix A. Data and Sample Construction

DATA SOURCES

Clean energy patent counts are obtained from the International Energy Agency (IEA) Energy Technology Patents database.1 We use the IEA's aggregate measure of clean energy patents by country and year to avoid double counting across patent offices. Consistent with the IEA methodology, patents with inventors located in multiple countries are fractionally allocated according to the inventors' country of residence.

Public energy R&D expenditures are also drawn from the IEA Energy Technology RD&D Budgets database and are reported in constant 2024 prices and purchasing power parity (PPP) terms. The data are compiled from national, federal, and central government budget sources. We aggregate expenditures across the following categories: energy efficiency; renewable energy sources; nuclear fission and fusion; hydrogen and fuel cells;

other power and storage technologies; and other cross-cutting technologies and research. Expenditures related to fossil fuels and unallocated spending are excluded.[2]

Greenhouse gas emissions data are taken from the OECD greenhouse gas emissions inventories. Emissions are measured in metric tonnes of CO -equivalent and exclude emissions from land use, land-use change, and forestry (LULUCF).[3]

Macroeconomic controls include GDP per capita and total population, both obtained from the World Bank.[4] GDP per capita (PPP) is converted to constant 2024 prices using the U.S. GDP deflator from the World Bank to ensure consistency with the R&D expenditure series.[5]

Environmental policy is measured using the OECD Environmental Policy Stringency (EPS) index.[6] In addition to the overall EPS index, we use its market-based and non-market-based subindices. The technology support subindex is excluded because it includes upstream R&D support, which overlaps conceptually with our measure of public energy R&D expenditures and would introduce collinearity.

To account for domestic energy cost conditions, we include the energy component of the OECD Consumer Price Index (CPI), obtained from the OECD Main Economic Indicators database (Consumer Price Index: OECD Groups – Energy [fuel, electricity, and gasoline], 2015 = 100). This index captures within-country variation in retail energy prices and serves as a proxy for energy price incentives that may influence clean energy innovation. Annual observations are used for all countries except Australia, for which annual data are not available. In the case of Australia, quarterly observations are averaged to construct annual values.[7]

To control for general innovation cycles unrelated to clean energy, we construct a measure of non-energy patent activity using annual IP5 patent family data by technology.[8] The IP5 comprises the European Patent Office, the Japan Patent Office, the United States Patent and Trademark Office, the Korean Intellectual Property Office, and the China National Intellectual Property Administration. We subtract patents classified as climate change mitigation or greenhouse gas capture and storage from total IP5 patents to obtain a measure of non-clean-energy-related patenting by country and year.

SAMPLE CONSTRUCTION

To maximize consistency across variables, the sample period is restricted to 2000–2020. With the exception of public R&D expenditures, data coverage is largely complete across countries during this period.

For public R&D spending, isolated gaps of up to three consecutive years are linearly interpolated. Results are substantively unchanged when these interpolated observations are excluded. Countries with fewer than thirteen years of observed public R&D data are excluded to ensure sufficient within-country variation for fixed-effects estimation.

After applying these restrictions, the final estimation sample consists of the following 23 countries observed over 2000–2020: Australia, Austria, Belgium, Canada, Switzerland, Czech Republic, Germany, Denmark, Spain, Finland, France, United Kingdom, Hungary, Ireland, Italy, Japan, South Korea, Netherlands, Norway, Poland, Sweden, Turkey, and the United States.

Table A1.

Descriptive Statistics

Variable	Observations	Mean	Standard Deviation
ln(Public clean energy R&D)	451	5.67	1.45
ln(Clean energy patents)	482	4.93	1.85
ln(Total emissions)	483	12.44	1.27
ln(GDP per capita)	483	10.92	0.34
ln(Population)	483	16.96	1.17
EPS index	483	2.79	0.81
Market-based EPS index	483	1.53	0.88
Non-market-based EPS index	483	4.61	1.17
ln(Non-energy patents)	483	7.51	1.68
Energy price index	483	89.88	19.62

Appendix B. Statistical Properties and Diagnostic Tests

UNIT ROOT TESTS

We evaluate the time-series properties of the panel using three commonly applied panel unit root tests: Im–Pesaran–Shin (IPS), Maddala–Wu (MW), and Pesaran's cross-sectionally augmented IPS (CIPS) test.[9] The IPS and Maddala–Wu procedures assume cross-sectional independence, while the CIPS test explicitly accounts for cross-sectional dependence. Table B1 reports test statistics for the variables evaluated.

For the main innovation variables, logged public clean energy R&D expenditures and logged clean energy patents, all three tests reject the null hypothesis of a unit root at conventional significance levels, suggesting stationarity in levels.

Results for macroeconomic controls and emissions are more mixed. The IPS and Maddala–Wu tests frequently reject the unit root null for GDP per capita, population, and emissions. However, the CIPS test, which accounts for cross-sectional dependence, does not consistently reject the unit root hypothesis for these variables. Similar mixed evidence is observed for the energy price index and the market-based EPS measure.

Table B1.

Panel Unit Root Tests

	Im, Pesaran, and Shin (2003)	Maddala and Wu (1999)	Pesaran (2007)
	t-statistic	χ^2 statistic	t-statistic
ln(Public clean energy R&D)	-3.27***	130.51***	-3.39***
ln(Clean energy patents)	-3.09***	80.03***	-3.20***
ln(Total emissions)	8.33***	18.3***	-2.57
ln(GDP per capita)	-1.77*	74.61***	-1.43
ln(Population)	3.70***	63.85***	-1.88
EPS index	-1.87	67.41***	-3.17***
Market-based EPS index	1.76	56.50***	-2.37
Non-market-based EPS index	-123.12***	605.08***	-4.76***
ln(Non-energy patents)	-4.64***	124.23***	-2.16*
Energy price index	-0.91	53.68***	-2.21

Note: Reported values are test statistics. For the Im, Pesaran, and Shin (2003) and Pesaran (2007) tests, more negative values indicate stronger rejection of the unit-root null. For the Maddala and Wu (1999) test, larger χ^2 values indicate rejection. The tests include individual country level intercepts and a linear time trend. *p<0.1; **p<0.05; ***p<0.01.

SERIAL CORRELATION AND CROSS-SECTIONAL DEPENDENCE

To assess the robustness of the fixed-effects and first-difference specifications, we conduct two standard panel diagnostics. First, we test for serial correlation in the idiosyncratic error term using the panel Breusch–Godfrey (PBG) test.[10] The null hypothesis is no serial correlation of order one in the residuals. Second, we test for cross-sectional dependence using Pesaran's CD statistic.[11] The null hypothesis is cross-sectional independence of residuals.

Across specifications, the emissions regressions exhibit both serial correlation and statistically significant cross-sectional dependence. The patents-on-R&D regressions show consistent serial correlation, while cross-sectional dependence appears primarily in levels specifications and is largely absent in first-difference models.

Given these findings, the analysis reports standard errors robust to heteroskedasticity, serial correlation, and cross-sectional dependence (Driscoll–Kraay corrections).[12]

Table B2.

Serial Correlation and Cross-Sectional Dependence Diagnostics

PANEL A. PATENTS ON R&D

	Specification				
Test	(1) Baseline	(2) Econ + Policy	(3) Non-Energy Patents + Energy Price Index	(4) Market-Based Policy	(5) Non-Market-Based Policy
PBG (χ^2)	27.31***	27.21***	28.57***	32.80***	27.95***
Pesaran CD (z)	-1.96**	-2.00**	-1.86*	-1.78*	-1.74*

PANEL B. FIRST-DIFFERENCED PATENTS ON R&D

	Specification				
Test	(1) Baseline	(2) Econ + Policy	(3) Non-Energy Patents + Energy Price Index	(4) Market-Based Policy	(5) Non-Market-Based Policy
PBG (χ^2)	69.97***	72.45***	71.40***	71.48***	70.89***
Pesaran CD (z)	-0.20	-0.05	0.04	0.08	0.01

PANEL C. EMISSIONS ON PATENTS

	Specification				
Test	(1) Baseline	(2) Econ + Policy	(3) Non-Energy Patents + Energy Price Index	(4) Market-Based Policy	(5) Non-Market-Based Policy
PBG (χ^2)	149.33***	133.96***	104.52***	101.72***	96.73***
Pesaran CD (z)	-2.27**	-2.16**	-2.23**	-2.09**	-2.36**

PANEL D. FIRST-DIFFERENCED EMISSIONS ON PATENTS

	Specification				
Test	(1) Baseline	(2) Econ + Policy	(3) Non-Energy Patents + Energy Price Index	(4) Market-Based Policy	(5) Non-Market-Based Policy
PBG (χ^2)	26.83***	24.61**	24.77***	24.97***	24.98***
Pesaran CD (z)	-2.40**	-2.40**	-2.41**	-2.41**	-2.42**

Note: PBG reports the panel Breusch–Godfrey test for serial correlation (Breusch, 1978; Godfrey, 1978; Baltagi, 2005). Pesaran CD reports the cross-sectional dependence test (Pesaran, 2004). *p<0.1; **p<0.05; ***p<0.01.

Appendix C. Full Regression Results

Table C1.

Patents on R&D

	Dependent variable:				
	Δln(Clean energy patents)				
	(1)	(2)	(3)	(4)	(5)
ln(Public clean energy R&D) $_{t-5}$	0.068	0.082**	0.091***	0.088***	0.072***
	(0.043)	(0.039)	(0.029)	(0.027)	(0.024)
ln(GDP per capita)		0.431	0.393	0.487	0.482
		(0.356)	(0.387)	(0.32)	(0.372)
ln(Population)		0.861	0.769	0.334	0.485
		(1.233)	(1.094)	(0.904)	(1.113)
EPS index $_{t-5}$		-0.111**	-0.106**		
		(0.054)	(0.05)		
Energy price index $_{t-5}$			-0.005	-0.004	-0.005
			(0.005)	(0.004)	(0.005)
ln(Nonenergy patents)			0.207	0.244	0.236
			(0.172)	(0.175)	(0.174)
Marketbased EPS index $_{t-5}$				-0.453***	
				(0.093)	
ln(Public clean energy R&D) $_{t-5}$ x				0.073***	
				(0.013)	
Nonmarketbased EPS index $_{t-5}$					-0.008
					(0.104)
ln(Public clean energy R&D) $_{t-5}$ x					0.0004
					(0.016)
Observations	341	341	341	341	341
R^2	0.019	0.052	0.064	0.082	0.051

Note: $^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table C2.

First-Differenced Patents on R&D

	Dependent variable:				
	Δln(Clean energy patents)				
	(1)	(2)	(3)	(4)	(5)
Δln(Public clean energy R&D) $_{t-5}$	0.106**	0.115**	0.117**	0.120**	0.119**
	(0.046)	(0.048)	(0.048)	(0.048)	(0.055)
Δln(GDP per capita)		0.516	0.352	0.212	0.307
		(0.465)	(0.456)	(0.432)	(0.434)
Δln(Population)		-0.035	0.107	-0.09	0.116
		(1.605)	(1.586)	(1.352)	(1.673)
ΔEPS index $_{t-5}$		-0.044	-0.032		
		(0.084)	(0.081)		
ΔEnergy price index $_{t-5}$			0.002	0.001	0.002
			(0.005)	(0.004)	(0.005)
Δln(Nonenergy patents)			0.294	0.326	0.306
			(0.199)	(0.198)	(0.2)
ΔMarketbased EPS index $_{t-5}$				-0.086	
				(0.087)	
Δln(Public clean energy R&D) $_{t-5}$ x				-0.223	
				(0.188)	
ΔNonmarketbased EPS index $_{t-5}$					0.026
					(0.035)
Δln(Public clean energy R&D) $_{t-5}$ x					-0.045
					(0.122)
Observations	317	317	317	317	317
R^2	0.121	0.123	0.129	0.14	0.13

Note: *p<0.1; **p<0.05; ***p<0.01.

Table C3.

Emissions on Patents

	Dependent variable:				
	Δln(Clean energy patents)				
	(1)	(2)	(3)	(4)	(5)
ln(Public clean energy R&D) $_{t-5}$	0.003	-0.007	-0.020**	-0.020***	-0.017**
	(0.015)	(0.006)	(0.008)	(0.007)	(0.008)
ln(GDP per capita)		0.631***	0.452***	0.460***	0.463***
		(0.17)	(0.122)	(0.119)	(0.117)
ln(Population)		0.667*	0.818**	0.788**	0.860**
		(0.382)	(0.323)	(0.345)	(0.354)
EPS index $_{t-5}$		0.033***	0.024*		
		(0.012)	(0.013)		
Energy price index $_{t-5}$			0.0001	0.001	0.0001
			(0.001)	(0.001)	(0.001)
ln(Nonenergy patents)			0.099***	0.104***	0.114***
			(0.03)	(0.026)	(0.028)
Marketbased EPS index $_{t-5}$				-0.054	
				(0.058)	
ln(Public clean energy R&D) $_{t-5}$ x				0.011	
				(0.013)	
Nonmarketbased EPS index $_{t-5}$					-0.01
					(0.016)
ln(Public clean energy R&D) $_{t-5}$ x					0.004
					(0.003)
Observations	298	298	298	298	298
R^2	0.001	0.411	0.489	0.489	0.497

Note: *p<0.1; **p<0.05; ***p<0.01.

Table C4.

First-Differenced Emissions on Patents

	Dependent variable:				
	Δln(Clean energy patents)				
	(1)	(2)	(3)	(4)	(5)
Δln(Public clean energy R&D) $_{t-5}$	0.002	0.003	0.003	0.003	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Δln(GDP per capita)		0.524***	0.522***	0.523***	0.521***
		(0.132)	(0.144)	(0.148)	(0.144)
Δln(Population)		0.659*	0.647**	0.636*	0.642*
		(0.354)	(0.328)	(0.328)	(0.334)
ΔEPS index $_{t-5}$		0.008	0.008		
		(0.005)	(0.005)		
ΔEnergy price index $_{t-5}$			0.0005*	0.001**	0.0004
			(0.0003)	(0.0002)	(0.0003)
Δln(Nonenergy patents)			-0.006	-0.004	-0.006
			(0.018)	(0.017)	(0.019)
ΔMarketbased EPS index $_{t-5}$				0.005	
				(0.008)	
Δln(Public clean energy R&D) $_{t-5}$ x				0.01	
				(0.017)	
ΔNonmarketbased EPS index $_{t-5}$					0.003
					(0.003)
Δln(Public clean energy R&D) $_{t-5}$ x					-0.003
					(0.003)
Observations	275	275	275	275	275
R^2	0.437	0.533	0.535	0.535	0.535

Note: *p<0.1; **p<0.05; ***p<0.01.

Appendix Endnotes

1 IEA, “Energy Technology Patents Data,” https://www.iea.org/data-and-statistics/data-tools/energy-technology-patents-data-explorer.

2 IEA, “Energy Technology RD&D Budgets,” https://www.iea.org/data-and-statistics/data-product/energy-technology-rd-and-d-budget-database-2.

3 OECD, “Air Emissions - Greenhouse Gas Emissions Inventories,” https://data-explorer.oecd.org/.

4 World Bank, “GDP per capita, PPP (constant 2021 international $)”, https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.KD; and World Bank, “Population, total,” https://data.worldbank.org/indicator/SP.POP.TOTL.

5 World Bank, “GDP deflator: linked series (base year varies by country)”, https://data.worldbank.org/indicator/NY.GDP.DEFL.ZS.AD.

6 OECD, “OECD Environmental Policy Stringency Index,” https://data-explorer.oecd.org/.

7 OECD, *Main Economic Indicators Database*, Consumer Price Index: OECD Groups: Energy (Fuel, Electricity, and Gasoline, 2015 = 100).

8 OECD, “Patents by Technology,” https://data-explorer.oecd.org/.

9 M. Hashem Pesaran, “A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence,” *Journal of Applied Econometrics* 22, no. 2 (2007): 265–312, https://doi.org/10.1002/jae.951; G. S. Maddala and Shaowen Wu, “A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test,” *Oxford Bulletin of Economics and Statistics* 61, no. S1 (1999): 631–52, https://doi.org/10.1111/1468-0084.0610s1631; Kyung So Im et al., “Testing for Unit Roots in Heterogeneous Panels,” *Journal of Econometrics* 115, no. 1 (2003): 53–74, https://doi.org/10.1016/S0304-4076(03)00092-7.

10 T. S. Breusch, “Testing for Autocorrelation in Dynamic Linear Models*,” *Australian Economic Papers* 17, no. 31 (1978): 334–55, https://doi.org/10.1111/j.1467-8454.1978.tb00635.x; L. G. Godfrey, “Testing for Higher Order Serial Correlation in Regression Equations When the Regressors Include Lagged Dependent Variables,” *Econometrica* 46, no. 6 (1978): 1303–10, https://doi.org/10.2307/1913830; Badi H. Baltagi, *Econometric Analysis of Panel Data*, Springer Texts in Business and Economics (Springer International Publishing, 2021), https://doi.org/10.1007/978-3-030-53953-5.

11 M. Hashem Pesaran, “General Diagnostic Tests for Cross Section Dependence in Panels,” *IZA Discussion Paper No. 1240*, ahead of print, 2004, https://doi.org/10.2139/ssrn.572504.

12 John C. Driscoll and Aart C. Kraay, “Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data,” *The Review of Economics and Statistics* 80, no. 4 (1998): 549–60.