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Knowledge spillovers from clean and emerging technologies in the UK

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Knowledge spillovers from clean and emerging technologies in the UK

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Abstract
The UK government has committed to increase R&D support for clean technologies in an effort to meet its net-zero target by 2050. The opportunity cost of such programs crucially depends on the value of knowledge spillovers that accrue from clean relative to other (emerging) technologies. Using patent information to measure the value of direct and indirect knowledge spillovers, we derive estimates for the expected economic returns of subsidising a particular technology field. Our method allows comparing fields by the returns a hypothetical additional subsidy would have generated within the UK or globally. Clean technologies are top-ranked in terms of within-UK returns, with Tidal and Offshore Wind showing particularly high returns. In terms of global returns, emerging technologies such as Wireless, as well as Electrical Engineering outperform Clean by a small margin. We also find that cross-border knowledge spillovers are important for all technology fields, with global return rates over ten times larger than within-UK ones. In sum, our results suggest that the opportunity cost of R&D support programs for clean innovation in the UK is low at worst.

Key words: innovation, knowledge spillovers, clean technology, innovation policy, patent data

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1. Introduction

The UK government is committed to reducing greenhouse gas emissions to net-zero by 2050. Increasing government support for R&D in clean technology is an essential part of the strategy to achieve this target, whilst maintaining a commitment to increase overall R&D spending to 2.4% of GDP. Understanding how public R&D can induce innovation-led growth, including relative differences between technological fields and sectors, is important when making decisions on how to allocate finite public resources.

In this paper, we inform this debate by comparing the returns that subsidies are expected to create across technological fields taking into account both the direct return to innovators as well as knowledge spillovers. Knowledge spillovers are a principal source of market failure for innovation (Arrow, 1962). They happen when the knowledge embedded in one innovation has a value to future innovations. As such, spillovers create value that is not reaped by the innovator, leading to underinvestment in R&D from a societal perspective. R&D subsidies address this market failure by increasing private incentives to innovate. If total returns differ between technological fields, re-allocating public resources to the fields with the highest returns can increase the effectiveness of R&D subsidies. We will examine how such returns differ between various clean technologies and compare clean technologies as a whole with other emerging technologies.

To measure innovation by UK inventors, we rely on the EPO PATSTAT database, the most comprehensive collection of patent documents available. We define the total economic value of innovation as the sum of its private value – i.e. the increase in profits due to the innovation – and its spillover value – i.e. the economic value it creates to society by inducing knowledge spillovers. To estimate private value, we use a predictive model of a firm's stock-market reaction when obtaining a patent right. This model allows us to extrapolate the stock-returns-based measure – which is only available for listed firms – to the population of patented inventions. To track knowledge spillovers, we use the fact that inventors are required to disclose which prior patents are relevant to their invention. To measure the value of knowledge spillovers, we assume that a portion of an invention's value derives from spillovers induced by the inventions it cites.

These metrics for private and spillover value allow us to rank fields in terms of how much value they create to society on average. However, to calculate returns to subsidies, we need estimates of how costly it is to innovate in a field – i.e. how many innovations a certain subsidy amount can 'buy'. In addition, we need to account for the fact that subsidies mainly induce innovations that would not have been pursued based on their expected private returns only. We take this into account using an economic model of the innovation process that allows us to construct an indicator for the expected rate of return to a subsidy in a specific technological field.

We implement our methodology on the population of innovations originating in the UK between 2005 and 2014. This window is the latest we can reliably study, given the available data. Further analysis shows that the rates of returns we estimate are reasonably stable over time. Therefore, the results are likely indicative of the returns that can be expected from current support policies.

Our results indicate that clean innovation fields in the UK rank highly in expected returns to subsidy, realising about 50% higher returns than broad fields such as Electrical Engineering, Instruments, Mechanical Engineering and Chemistry . We also benchmark clean technology sub-fields against 'trending' fields such as Artificial Intelligence and Biotechnology. Results show Tidal Stream and Offshore Wind at the top of this ranking. CCUS, Smart Systems and Building fabric also score above average, while Biomass & Bioenergy and Solar score below average.

Based on our analysis, we expect that a clean technology support programme of £10M granted between 2005 and 2014 would have created economic spillover returns of £330K to the UK economy in that same period; i.e. a return of 3.3%. The same programme would have created returns of £3.7M to the global economy through cross-border knowledge spillovers; i.e. a return of 37%. It is important to note that these returns pertain to the expected value of projects that would not have been carried out in the absence of the support programme. The estimated average return rate for UK clean R&D that would be performed regardless of any subsidy is about 75%.

The 3.3% within-UK return rate to Clean R&D support is a lower bound of the actual economic return rate for two reasons. First, knowledge spillovers take time to realise. The spillovers from innovations towards the end of our time window likely realise only after 2014. When analysing innovations between 2005 and 2009, thus allowing each innovation at least 5 years to realise spillovers, within-UK return rates are about 6% and global return rates are about 70%. This analysis still excludes spillovers realised post-2014. A further analysis suggests that innovations induce a significant amount of spillovers for at least 2 decades after their introduction. Of all spillovers that innovations from 1990 induced between 1990-2014, 15% are induced by 1995, 53% by 2000, 71% by 2005 and 86% by 2010, with yearly spillovers rates showing no decline towards the end of the sample period. Second, our model makes the conservative assumption that no additional market failures are corrected by the subsidies. Credit constraints due to imperfect capital markets, risk/uncertainty aversion and short-termism make it likely that firms underinvest in R&D projects with positive expected private returns. Subsidies can mitigate these frictions and therefore have higher returns than the ones we estimate.

We also examine differences in R&D subsidy returns by technology readiness level (TRL). Technologies with relatively low TRL are in the infant stages of their development, and therefore require a great deal of development before their economic benefits come into fruition. Being more generic, they could also provide spillovers to a larger number of follow-on innovations, and are therefore particularly underfunded by private firms. Investing in such technologies is risky for firms because their eventual success is uncertain and because it is unclear whether the innovator will be able to appropriate their ensuing value. Subsidy programmes can increase payoffs to these risky investments and therefore help induce firm investments in low-TRL technologies. If these technologies are indeed superior in terms of spillover value, supporting R&D in low-TRL technologies could be a particularly promising policy.

To assess the TRL of a technology, we use the detailed technological classes assigned to patents by the patent office. This classification is designed to help patent examiners establish the inventive step of an invention. Prior work has shown that inventions that combine classes that no patent before has combined are indeed more novel and display higher variation in technological success. We use this measure to gauge whether an invention was of low TRL.

The results show that clean technologies, on average, display lower TRL than most other fields. When breaking down the returns to subsidy by high or low TRL, clean technology produces the highest returns for both types, but the difference is larger for low-TRL-inventions. Returns to subsidy are about 30% higher for low-TRL-inventions.

In sum, our results suggest that shifting more public resources to clean technology R&D does not go at the expense of lower economic returns – as captured by private and spillover value of innovations within the UK. However, we also identify substantial heterogeneity across clean technology classes with Tidal Stream, Offshore Wind, CCUS, Smart Systems and Building Fabric technologies showing particularly high levels of return. We also find heterogeneity at the national and international level, with considerably larger spillover effects when cross-border innovation effects are included. It could also be particularly fruitful to combine a strategy to support clean technologies with a focus on low TRL clean technologies to maximise economic returns. Such considerations would need to be balanced to meet technology requirements for Net Zero by 2050, which may also require mid/high TRL innovations to be scaled and commercialised in parallel.

Despite an extensive body of literature documenting the importance of knowledge spillovers, we know relatively little about the variation in knowledge spillovers between detailed technology groups. Much of the literature is instead focused on specific types of technologies, on average effects for the economy as a whole or on distinctions between basic research and more close to market research (Griliches, 1992, 1986).

Methodologically, most work has used patent data to come to grips with the importance of knowledge spillovers (Scherer, 1965; Griliches, 1991; Jaffe, 1986). One common approach is to estimate the cross-elasticity of R&D activity between firms that are close in technological or geographic space (Bernstein & Nadiri, 1989; Jaffe et al., 1993; Bloom et al., 2013). The idea behind this approach is that, in the presence of knowledge spillovers, pursuing innovation becomes more profitable when related firms do so as well. This results in a positive relationship between similar firms' R&D activities, which is used to gauge the importance of knowledge spillovers. In an attempt to more closely observe spillover links between innovation projects, patent citations have become an important methodological tool to measure knowledge spillovers (Trajtenberg, 1990; Alcacer & Gittelman, 2006). The assumption behind this approach is that when a patented invention makes reference to previous inventions, it has 'received' knowledge spillovers from these inventions. Most commonly, the number of patent citations received from future inventions is used as a measure of the magnitude of spillovers induced.

While methods that estimate cross-elasticities using innovation production functions of firms offer plausible estimates of the value of spillovers, they lack the flexibility to be applied on the granular level relevant to industrial policy. Specifically, they need to control for various economic factors – for instance demand – that also result in a positive correlation between similar firms' R&D activities. This requires specific datasets and settings which makes the approach too inflexible to be applied at the level of detail necessary for the task set out in this report. Forward citation counts address this issue and give a detailed account of the knowledge linkages between innovations. However, they do not give an objective value measure comparable across technological categories because they do not take into account the value of the citing patents. The approach we use addresses both issues by providing a monetary value of knowledge spillovers on the level of a patented innovation. In addition, our methodology accounts for private value differences between innovations when estimating knowledge spillovers. Moreover, it takes into account indirect spillovers arising from innovations at a more distant location in the citation network.

A few prior studies have used patent data and forward citations to investigate knowledge spillovers by Clean technologies. Dechezlepretre et al (2014) documented that Clean innovations tend to produce vastly more knowledge spillovers than comparable "dirty" ones. This work has been refined in Guillard et al (2021), Rydge et al (2018), Martin et al (2020a) and Martin et al (2020b) who show that there are significant differences in spillover rates between different clean technology types. Moreover, the ranking of these rates varies between different countries. Finally, the ranking of technologies based on return rates changes when only considering the spillovers that realise within a country (national spillovers) as compared to considering all spillovers induced (global spillovers).

2. Background

The UK government is committed to reducing UK greenhouse gas emissions to net-zero by 2050. For that purpose, the government is designing a Net Zero Innovation Portfolio. There has been extensive research into which clean technologies are most promising and effective in reducing both UK and global emissions. As societal benefits from emission-reducing innovations are only partially captured in the profits of innovators, R&D support is a crucial component to achieve socially optimal levels of clean technology development.

However, government support for innovation is also an important driver of economic growth. Indeed, long-run economic growth comes from advances in technology and practices that derive from research and innovation. Public resources used to support clean technology development are, by definition, not used to subsidise other areas of innovative activity. If these other areas produce higher economic returns to subsidy, there is a clear trade-off between achieving net zero and stimulating economic growth. If clean areas are in fact competitive regarding the returns to subsidy, such a trade-off does not exist. This would open up the potential to design a Net Zero Innovation Portfolio that is both GHG mitigating and growth-enhancing.

To a large extent, public investment in innovative activities is motivated by the existence of knowledge spillovers. Knowledge is a public good in the sense that once an insight has been achieved it can be easily copied or it will generate new insights by others who have not participated in the financing of the R&D that brought about the original insight. Because of such knowledge spillovers it is widely accepted that market forces alone will underprovide investment in R&D and government support for R&D will be most effectively spent if it is targeted towards those types of innovation that generate more knowledge spillovers than others. For instance, we expect higher knowledge spillovers when it comes to more basic research and in technology areas that are more general purpose in nature. Oftentimes, government support for R&D is structured accordingly.

As knowledge spillovers are the key argument to justify government support for innovation, it is crucial to understand the value of knowledge spillovers in clean technology as compared to other fields of innovation. In this report we use a comprehensive analysis of global innovation data along with information on knowledge flows to estimate the value of knowledge spillovers created by innovations.

Our methodology captures all economic value created by innovation that enters the profits of a firm. We estimate these private returns using a model that fits patent metrics to stock-market reactions when a patent is granted. This measure is a proxy for how much value the innovator appropriated from its innovation.

To estimate the value of knowledge spillovers, we assign a portion of the private returns reaped by future innovators, building directly or indirectly upon an innovation, as the value of knowledge spillovers induced by a focal innovation. To track spillover links, we make use of the fact that innovators are required to cite prior art when applying for a patent. The network defined by these patent citations allows us to account for both direct and indirect knowledge flows between innovations.

Our measure values knowledge spillovers by innovations that are created regardless of additional government support. However, the innovations that happen in response to a subsidy may have different returns than the ones we observe. Indeed, the subsidy-induced innovations are those that would not have been pursued based on their expected private returns only. The spillovers created by these innovations may differ from those created by the innovations that would have happened anyways. In addition, any given subsidy amount will result in different 'amounts' of innovation based on the field-specific costs of innovating. We implement a methodology that addresses these issues by accounting for variation in the responsiveness of different technology fields to government support. Specifically, we use the observed private returns distribution in a field to infer the cost of pursuing an innovation, and the economic returns of subsidy-induced innovations. We use these estimates to construct a measure for the rate of return to a subsidy in a particular technology field.

We calculate our metrics for various, broadly defined technological fields. In addition, we benchmark specific clean technology fields – e.g. Tidal Stream or Offshore Wind – to fields often considered to be high-potential for future growth – e.g. Biotechnology or Artificial Intelligence. To provide insights relevant for UK policy making we take into account the specific innovation landscape of the UK. We focus on innovation produced by inventors residing in the UK and examine the value of knowledge spillovers realized within the UK.

To examine the potential of R&D support programmes that focus on technologies that are in the early stages of technology development, we compare our return-to-subsidy indicator for innovations with a proxy for high and low 'technology readiness levels' (TRL). To classify the TRL-level of an innovation, we use an indicator of technological novelty that leverages the fact that most (radically) novel innovations make completely new connections between clusters of knowledge. Such novel innovations require longer times to realize their value and are riskier for firms to pursue. As such, they can be seen as having low levels of TRL and be used to examine the potential of targeting subsidies to low-TRL innovation projects.

3. Methods

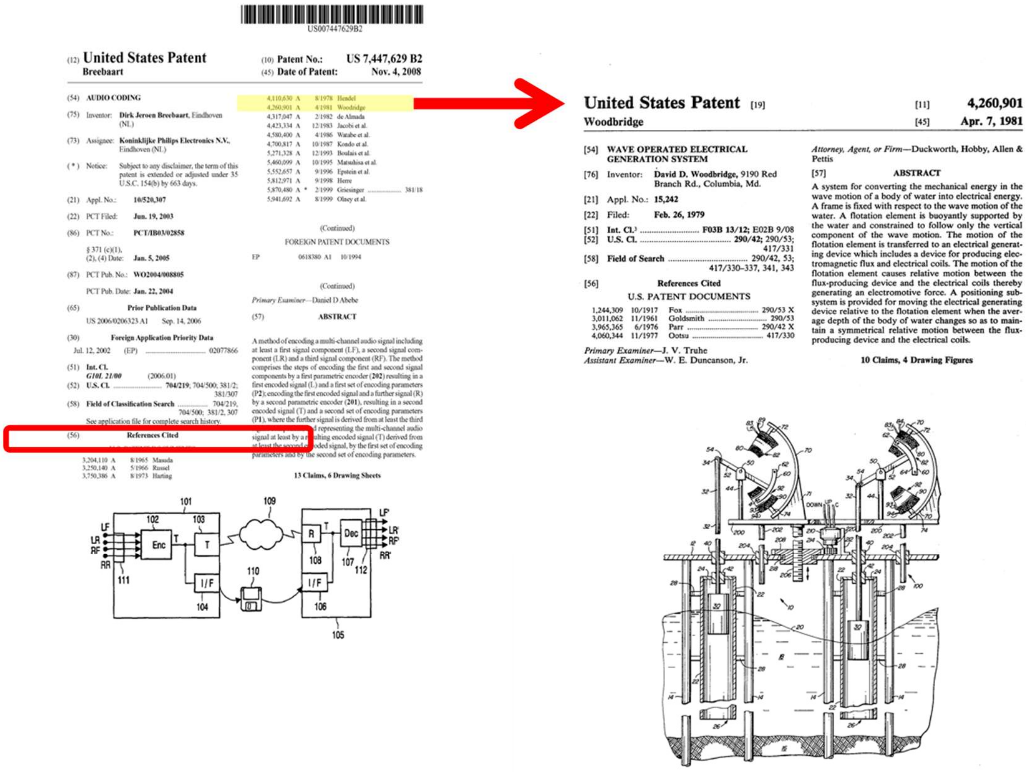
3.1 Measures

We rely on the methodology developed in Guillard et al (2021) to estimate the value of specific innovations. We also develop an indicator that allows ranking the return to public subsidies for different technology types. Here we provide a brief summary of the underlying methodology. We rely on global patent information from the PATSTAT database which we combine with data on firms from the Orbis Global database.

To identify an innovation we rely on patent families identified in PATSTAT. When protecting an invention, an organization needs to file patent applications in all jurisdictions it seeks protection in. As such, one invention is often related to multiple patent applications. A patent family consists of all patent applications related to the same innovative step. For each patented innovation, the database contains various relevant pieces of information extracted from patent documents that are published during the examination process. We use information on technological classes (using the Cooperative Patent Classification scheme, or CPC), patent citations, patent claims (detailing what precisely is sought to be protected by the patent), time of filing, the number of patent applications related to the invention, the applicant name (the person or organization that will own the patent right) and the address of the inventors on the patent. We use the Orbis database to obtain a harmonized identifier of applicants across different patent families.

We capture spillover links between innovations by the standard approach in economics to use citations present on the front page of patent documents. These citations are produced by the applicant and the patent examiner. They serve to position the 'contribution' of the invention as compared to the prior art of all previous inventions. These citations provide a 'paper trail' of knowledge linkages across different innovations. We use this information to identify which innovations benefit from the knowledge of the cited innovation. Therefore, patent citations can be used to construct a network of knowledge spillovers. Figure **1** shows an example of such a patent citation. On the left we see a US patent from 2008 on an improved approach for audio encoding citing a patent from 1981 for a wave energy device. Some of the mathematics required for the audio encoding was built on the mathematics developed for an efficient operation of the wave energy device.

Figure 1: Citation example



Notes: Example of a patent citation. Left-hand side patent (of which the front page is shown) cites right-hand side patent as relevant prior art.

To measure the economic value of knowledge spillovers as captured by patent citations, we develop Patent Rank (P-Rank). This measure is inspired by PageRank – Google's original algorithm for ranking web pages.[1] Instead of PageRank's approach to use hyperlinks between web pages, Patent Rank uses citations between patent documents to assign an index of importance to every invention using the entire citation network. In particular, we assume that any innovation i has a value of V_i that consists of the sum of its private value PV_i and external (i.e. spillover) value EV_i.

$$V_i = PV_i + EV_i$$

To derive a private value PV_i for every invention we rely on a two-step procedure. First, we use data from an event study approach developed by Kogan et al (2017) to infer the value of individual innovations from the change in the innovating firm's share price – relative to the market – around the time when an innovation was first granted a patent for the underlying invention.[2] In the second step we use those value estimates to predict invention monetary values

[1] Page et al (1999)

[2] Note that this assumes that the market is able to accurately predict future cashflows derived from a patent grant. While this is a strong assumption for any given patent, idiosyncratic errors induced by

based on a number of patent indicators that are known to correlate to private value and are observed for all innovations. This step circumvents the problem that only a small fraction of all innovations belong to stock-listed firms. The predictors we use are a combination of timing of application, technological classification, the number of patent filings in the family and the number of claims. For instance, consider a patent belonging to class A61K31 ('Medicinal preparations containing organic active ingredients'), filed for in 2006, having 5 claims and 7 filings in its family. The private value of this invention is the average of the stock-market-based value of all inventions with exactly these characteristics.[3]

The external value EV_i is a weighted average of the private value of all innovations that cite i either directly or indirectly. Because EV_i depends on the value of all innovations that cite i, the expression above defines a large system of equations that can be solved by an iterative algorithm.[4] Figure 2 shows the intuition of the Patent Rank measure. It presents a simple citation network where a first innovation A is cited (hence produced knowledge spillovers for) by innovations B and C, which in turn are cited by innovations D and E. Innovations D and E are not cited, and hence produce no spillover value. Therefore, their total value is equal to their private value. However, a portion of this total value is assigned to innovations B and C as their spillover value. This means that their total value is larger than their private value. The same holds for innovation A, whose value depends not only on the value of B and C, but also on the value of D and E. The portion of value that is assigned as a spillover to cited inventions is given by $(\sigma * V)/F$.

σ is the marginal contribution of spillovers to the value of an invention. It is the fraction of the value of any innovation that stems from spillovers. The exact value of this parameter is an important area for further research.[5] In prior work we find that different values change the exact return figures substantially (i.e. a higher value implies higher returns as indirect linkages are valued more highly). However, we find that the ranking of different innovations or fields of innovations in terms of their spillovers – which is the key interest of the current study - is stable across different assumptions for σ. Lacking explicit estimates for σ for the time being we rely on proxies in the existing literature. Aghion et al (2016) provide estimates of an innovation production function for clean car technologies. There, for clean car technologies they find elasticities of approximately similar size for the own and external knowledge stock contribution to the generation of new (clean) innovation. Inspired by this we set σ equal to 0.5 which would correspond to equal contribution by a firms own efforts and external effects.[6]

departing from this assumption are averaged out when considering groups of patents. Our predictive model in the second step
assigns an average stock-market-based value to a group of patents of at least 30, where group definitions are based on a combination of patent value predictors. As such, our method is robust to idiosyncratic errors produced by faulty predictions by the market.

[3] Analyses in Guillard et al. (2021) show that the private values based on our predictive model correlate well to the stock-market-based estimates in the sample for which both measures are available.

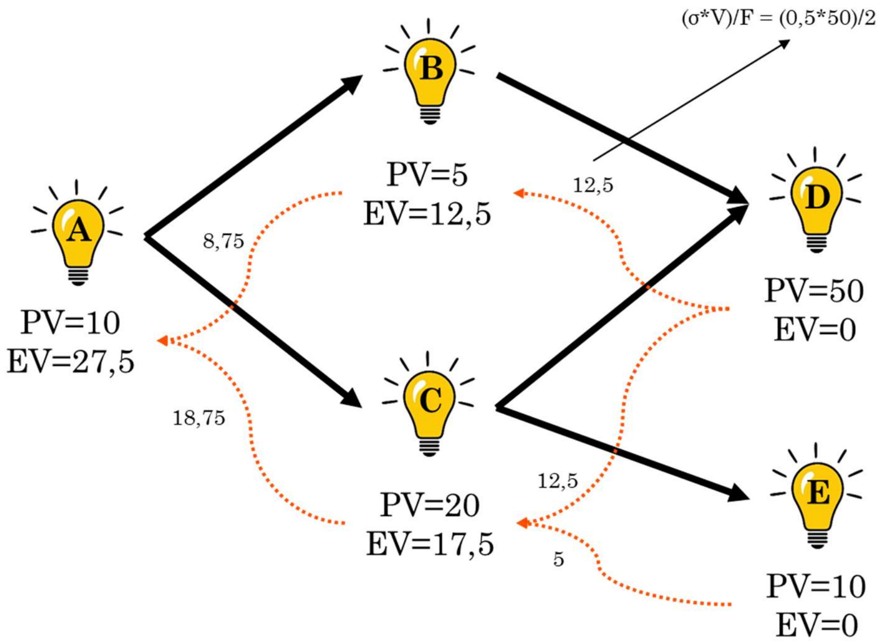
[4] For further detail see Guillard (2021).

[5] We hope to get more clarity about the most appropriate value for σ by embedding it in estimates of innovation production functions.

[6] However, we note that the same paper finds a smaller contribution for the spillover component in the creation of dirty technologies: the own component here is 4 times bigger than the spillover component

F is the number of patents that the innovation cites. We divide by F to correct for differences in citation practices between technological fields. Without this correction, fields where it is customary to cite many inventions would display particularly high spillovers that would only reflect such practices, rather than real spillover differences.

Figure 2: Intuition Patent Rank



Notes: Illustration of the Patent Rank algorithm. Patented innovation A is cited by innovations B and C. Innovation B is cited by D, and innovation C is cited by D and E. Black arrows represent the direction of knowledge spillovers. Orange dotted arrows show how Patent Rank assigns a spillover value to individual innovations based on the value of innovations that cite them.

Current approaches in the economics literature capture knowledge spillovers simply by counting the number of times the focal patent is cited by other patents as a measure of the 'amount' of spillovers generated. Our methodology addresses two key drawbacks of this approach.

First, whereas traditional measures assume that each citation represents the same spillover value, we integrate an estimate of the value of every innovation in our analysis. This implies that an innovation could be ranked higher if it is cited by innovations that are considered more valuable. In Figure 3 this is illustrated by invention A being cited by two low-value innovations B and D (as represented by the size of the bulb) and high-value innovation C.

Second, traditional measures do not account for the presence of indirect knowledge spillovers. In Figure 3, innovation A is cited 3 times. Our measure, however, also takes into account that those innovations themselves are cited, which affects the spillover value of innovation A.

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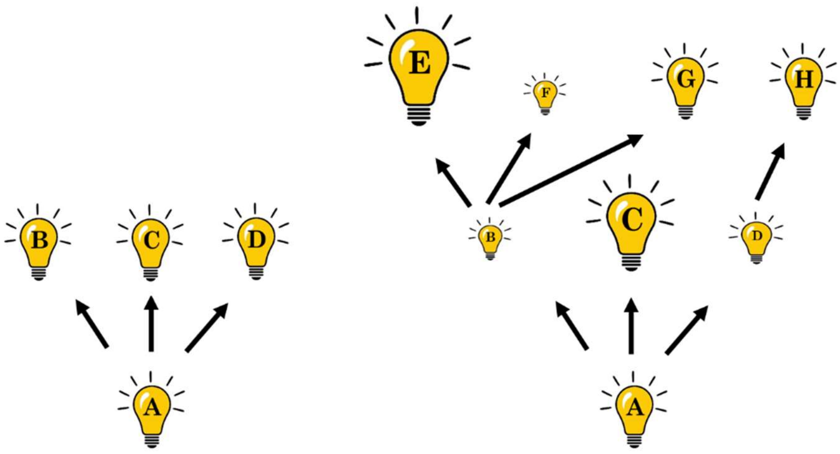
which would be more inline with a σ of 0.2. This would also suggest that in future work it could be useful to consider variable σ's across technology groups.

Figure 3: Comparison Patent Rank and forward citation count

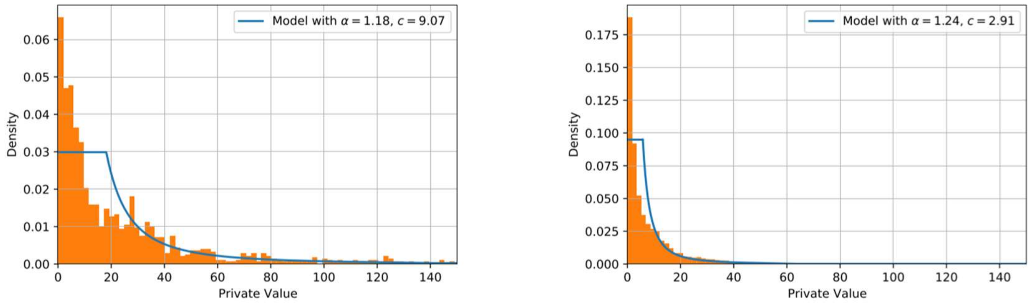


Given these new measures, we could compare fields in terms of value generated by innovations. However, such comparison would not be very informative for two reasons. First, the costs to innovate are likely to differ strongly between fields. While the innovation process proceeds in large steps with costly projects in Chemistry or Pharmaceuticals, it moves with smaller, less costly steps in fields like Computer technology or Semiconductors. Our value estimates are sensitive to these differences in costs, and therefore do not reflect returns to investments in a field. Second, additional subsidies to a field do not necessarily generate the ‘typical’ inventions we observe in the data. Indeed, firms use subsidies to decrease their cost of innovating. The innovation projects that are caused by additional subsidies are the projects that would have not been pursued based on their expected private returns alone. As such, it is quite likely that the returns to the subsidy-induced innovations are different from the returns we observe in the data.

To address these issues, we need measures for the costs of innovating in a field, as well as a projection of the value of subsidy-induced innovations. To obtain these estimates, we construct a model that characterizes innovator behaviour in a given technology field. We assume that the innovator observes ideas drawn from a left-skewed distribution – i.e. most ideas are not worth much, but some ideas are highly valuable. To create an innovation, the innovator needs to incur a fixed cost, after which she can reap its value which may turn out lower than expected. Fields differ in terms of how left-skewed their idea quality distribution is, and what are the costs to create an innovation from an idea. While we do not observe the ‘shape’ of the idea distribution or the costs of innovating, our model allows us to estimate REF distribution \h using the distribution of realized values of innovations. Figure 4 illustrates how our model fits realized private value distributions in two technology fields. This figure compares the two parameters – the cost of developing ideas (c_a) and the curvature of the idea quality distribution (α_a) – as estimated by our model (blue line) and as observed in the data (orange bars).[7]

Figure 4: Actual and modelled distributions of private value

(a) A61K (b) G06F



Notes: Actual and modelled distributions of the private value (PV) of innovation in the 'Preparations for medical, dental, or toilet purposes' technology category (A61K) and 'Electric digital data processing' (G06F). Blue line shows the modelled distribution given estimated parameter values. Orange bars show the distribution as observed in the data.

Using estimated costs c we can compute the average social return of a technology area a as the average social value minus the cost of developing ideas over the cost of developing ideas:

$$R_a = \frac{\bar{V}_a - c_a}{c_a} \quad (1)$$

e.g. a return of 10% would imply that for every £1B of R&D money spent there would be an economy wide return of £100M. These return figures are a correct representation of the return to additional government R&D spending if we assumed that all such spending would fully fund research projects that are entirely additional – i.e. projects that the private sector would not have engaged in without government support – and that such projects would be equivalent to the average quality of all current research projects both in terms of their private and external value. This is unrealistic in at least three respects: First, we would expect that projects with a positive profit have already been undertaken by firms. Second, because of information asymmetry, governments might not be able to distinguish between projects that would have gone ahead anyways and those that would not. Hence, at least some government funding might not be additional. Third, those projects that are additional might not be entirely government-funded; i.e. there might be marginal projects that firms would fund to a certain extent with some participation by government.

We can address the first concern by looking at returns in terms of spillover only (see **Figure 16**); i.e. this assumes that any additional project will provide value only via its external component.

$$EVR_a = \frac{\overline{EV_a}}{c_a} \quad (2)$$

To account for the other concerns outlined above we develop what we have dubbed the Industrial Strategy Index (IStraX). This indicator relies on the simple model of inventor behaviour discussed above to analyse the response by firms to an increase in government subsidy per project. Our model makes the conservative assumption that innovators would take a large amount of such an increase as a windfall gain on innovation projects they would have undertaken anyways. However, there would be some increase in the amount of innovation because inventors would start developing some ideas that were previously considered not sufficiently promising; i.e. those ideas just below the private-cost-threshold. Hence, this response will depend on the skewness of the idea generation distribution (a less skewed distribution will – all else equal – place more ideas just below the cost threshold). Our model estimates the value of the subsidy-induced innovation projects that are pursued given additional subsidies in a field. This value includes both the private and spillover value of additional projects.[8] IStraX also addresses another potential shortcoming of the measures suggested in equations 1 and 2. In both we are assuming that spillovers of any additional project correspond to the value of spillovers in the average project. However, because additional projects are of lower quality (in terms of their private value), their spillover potential might also differ.[9] In computing ISTRAX we estimate this difference from the spillover values of projects near the cut-off threshold.

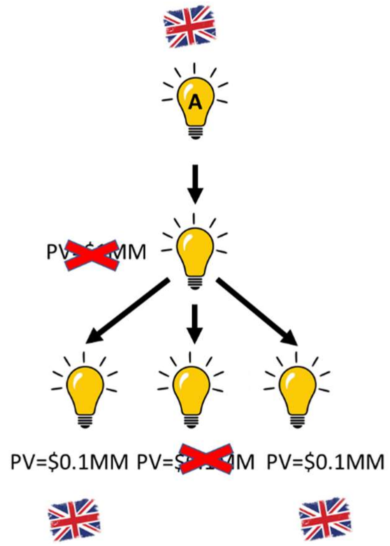
The nature of our spillover measure allows to distinguish between returns that are made at the national as opposed to global level. By definition, private returns from innovations originating at the national (here UK) level are returns reaped by a country. Spillovers, however, may flow to innovators within or across country borders. In addition, spillovers could flow outside the borders, but 're-enter' a country through indirect linkages in the citation network. As UK policymakers are likely most interested in the returns that are reaped within the UK, we compute IstraX by taking into account only spillovers retained within the UK. Figure **5** illustrates how we do this. Suppose we want to calculate the value of UK-based innovation A that is directly cited by a non-UK innovation, which itself is cited by two UK-innovations.[10] To capture UK spillovers from innovation A, we perform the P-Rank algorithm discussed above, but assign a value of zero to all non-UK inventions in the network. Doing this excludes the spillover value created across borders, but allows to capture spillovers captured by the UK through indirect network links. To allow for comparison, we also report IstraX when taking into account global instead of within-UK spillovers.

[8] Note that the contribution of the private value in this total value is very small because projects induced by the subsidy are those where the private value is close to the cost of executing the project, and hence will not be profitable for the firms pursuing them in the absence of a subsidy.

[9] Our approach is agnostic to the direction of this difference. On the one hand we might assume that projects with lower private value are also of lower social value. However, it could also be that lower private value projects are more fundamental which could motivate that they are of higher external value. Indeed this is what we find for most technology areas when looking at TRL below.

[10] We assign innovations to a particular country based on the location of the inventor (i.e. in the case of multinationals this might not necessarily be the headquarters of a company that owns the patent on the innovation).

Figure 5: Global vs. national spillovers



To assess the technology readiness level (TRL) of an innovation, we use an indicator of technological novelty developed in Verhoeven et al. (2016). The indicator is grounded in the observation that radically novel technologies – those with presumably low levels of TRL – are often the result of making completely new connections between previously existing components and clusters of knowledge.[11] The indicator uses detailed technological classes to represent these knowledge clusters. An innovation scores on the novelty indicator if its patent is the first to make at least one combination between classes for the first time. This indicator has been shown to identify a large number of expert-assessed, novel inventions. In addition, novel inventions are overrepresented in both tails of the technological success distribution, indicating their high-risk profile. We classify inventions identified as novel based on this indicator as being low in TRL, and those that do not score as being high in TRL.

3.2 Discussion of methods and data

While our approach has a number of distinct advantages over existing methods, a number of limitations remain and need to be taken into account when interpreting the results. In this section, we discuss some key advantages of our approach compared to prior work and highlight a number of limitations.

Most of the economics of innovation literature has measured the returns to R&D by counting the number of patents as an innovation output measure. However, it is widely accepted that there is large variation in the value distribution of patented innovations. To partially address this issue, some studies weight patent counts by the number of citations received. However, the number of citations received is a measure of technological, rather than commercial success, and therefore conflates private and social returns to innovation. Our approach explicitly

[11] For instance, the invention of the Oncomouse – a mouse that is genetically engineered to develop cancer – was the first technology that combined knowledge in genetic engineering to knowledge about using animal models for drug development. In doing so, this invention allowed tremendous advances in biomedical research by constructing an in vivo environment to test a wide range of drugs and treatments.

disentangles both sources of value and uses the best methods available to capture variation in the private value of innovations.

Next to being a tool to weight patent counts by quality, citation counts have been used to measure the spillovers created by innovation. However, these citation counts typically do not account for the value of the citing innovation, nor do they measure indirect knowledge spillovers by looking at the patent documents indirectly linked to the focal innovation. Our approach addresses these caveats and therefore produces more realistic measures of the value knowledge spillovers. In previous work, we show that our spillover measure produces vastly different rankings when compared to forward citation counts. In addition, our validation exercises suggest that our measure gives a more realistic account of knowledge spillovers induced by innovations.

A final advantage of our method is that, rather than using realised (spillover) returns to R&D to compare fields, we estimate the expected returns to additional subsidies in a field. This approach more realistically models economic behaviour of innovators in response to subsidies.

An important caveat to our methods is that we only observe innovations that are patented. Many innovations are not patented and are protected through secrecy or other intellectual property mechanisms. Our estimates do not account for this and will not offer a correct comparison between fields if their returns to non-patented innovation substantially differ from those to patented innovation.

Another concern with using patent data are two types of right-censoring. First, there is a considerable time lag in assembling all patent documents into the database we use because there is a lag between patent application and its resulting publication document (from which all patent-based information is derived). For PATSTAT, we observe a drop in the number of patent filings starting from 3 to 4 years before the end of the time window considered in the database. Because there might be differences between fields in how large this lag is, including these later years could result in truncation bias. This is why we report below results relying on data up until 2014. However, our earlier research suggests that there is a considerable degree of stability in the degree of spillover flows emerging from different technology types and countries. Nevertheless we suggest that this kind of analysis is regularly updated as the underlying patent databases are updated. The analyses performed in this report could be periodically updated to both monitor and guide industrial policy related to public R&D support.

A second type of right censoring concerns the timing of knowledge spillovers. In principle, one would have to wait indefinitely to truly register all spillovers created by innovation. In practice, we assume that the citations that materialise within the first couple of years after the occurrence of an innovation are a good predictor of its long run impact. In our results we report average returns across innovations with a varying time windows for accumulating citations. We show below that this has a considerable impact on the estimated absolute return figures. However, it has no impact on the relative ranking of different technologies.

A final limitation stems from the predicative ability of patent-based measures in a rapidly-evolving energy sector. Previous innovation fields may have yielded lucrative returns, but leave little room for further innovation. Conversely, lagging fields during our sample period may develop revolutionary changes and breakthrough innovations, as focus switches to new decarbonisation technologies. This is perhaps indicative of the rapid technological change and adoption of climate mitigating technologies observed over the past decade in many economies.

4. Results

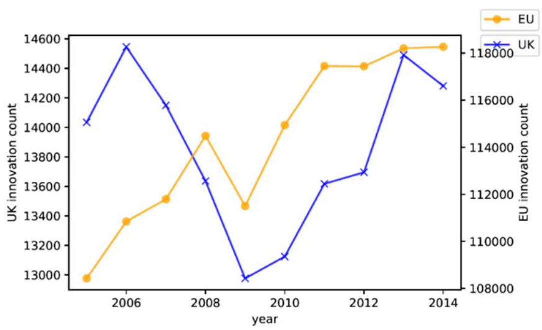
4.1 Trends in innovation

To set the scene, Figures **6** and **7** provide an overview of recent innovation performance – as measured via patented innovation – of the UK. The number of innovations filed by UK-based inventors fell by about 10% in the wake of the global financial crisis, from nearly 14,6K in 2006 to a low of about 13K in 2009. Innovation has since then recovered; however 2014 levels are still below the peak of 2006.

The drop in innovative performance of the UK is particularly stark when compared to other countries, namely those within the EU. While EU-countries also saw a drop in innovation post-recession, this was at most a dip on an otherwise steep growth path, rather than a sustained stagnation as in the UK.

Things look more positive for innovations by UK-based inventors classified as clean[12]: the number of such innovations increased continuously even after 2007. However, after 2011 the share of clean innovations in total innovations decreased. This is a global feature which has been pointed out by a number of papers (Popp et al 2020, Acemoglu et al 2019). There is an ongoing debate regarding the drivers of this. Candidate explanations include a declining price for fossil fuels, the discovery and development of shale gas and oil deposits and less appetite of financial markets for potentially more risky innovation projects.

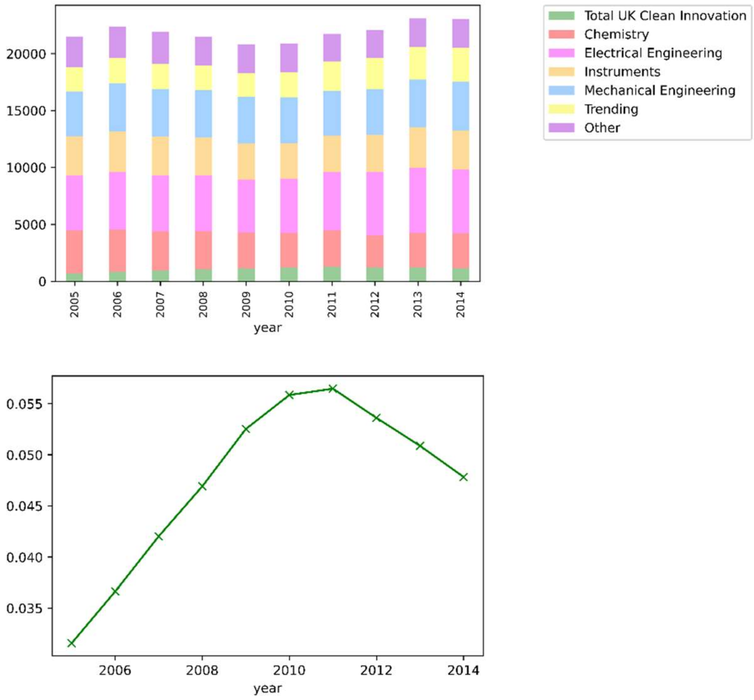
Figure 6: Comparison innovations UK and EU



Notes: Evolution of number of patented innovations for the UK (blue) and EU27 (yellow). We use the patent family as defined by the PATSTAT database as unit of analysis. Countries are assigned based on address information of inventors on patent documents.

[12] Here, we use the 'Y02-classification' developed by experts at the European Patent Office to tag climate-change-mitigating technologies.

Figure 7: Evolution UK innovations by field



Notes: Breakdown of the evolution of patented innovations in the UK by broad technological field (left) and the evolution of the share of Clean innovations in the UK (right). Technological fields are based on a mapping of technological classes on patent documents (CPC codes) to broad technology fields. For Chemistry, Electrical Engineering, Instruments, Mechanical Engineering and Others we use a mapping developed by the OECD (Schmoch, 2008). For Total UK Clean Innovation we use the 'Y02' class assigned to patent documents by experts at the European Patent Office (EPO). Category Trending includes a combination of a number of trending fields such as Artificial Intelligence, Biotechnology or 3D printing based on CPC codes that we selected manually. Because one innovation can belong to multiple categories, the total number of innovations on the left-hand-side graph exceeds the unique number of innovations in the UK from the previous figure.

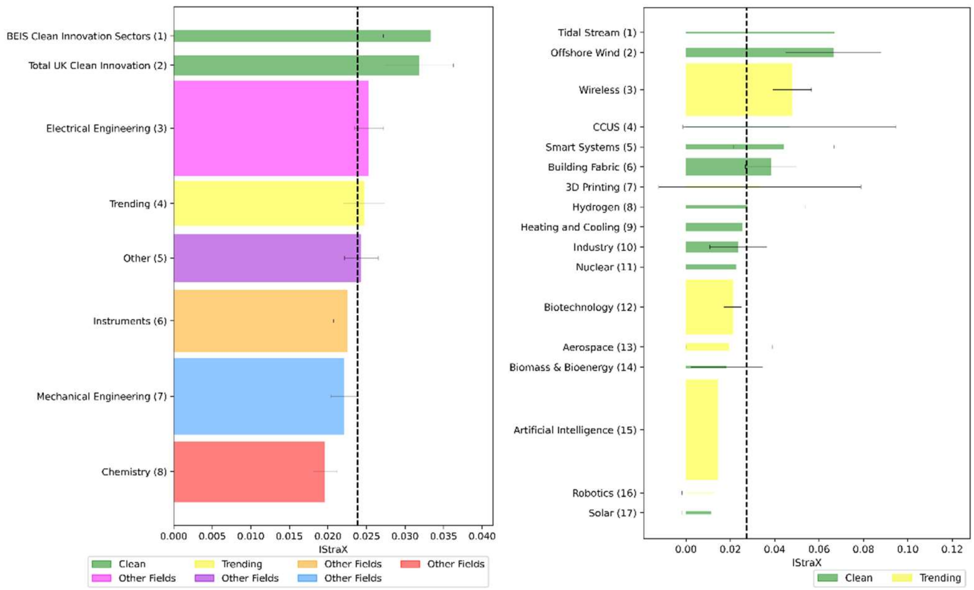
4.2 Returns to innovation

Figure **8** reports our main result: the within-UK social returns to R&D support for different technology types. The left panel reports returns for broad technology groupings. The right panel zooms in on the BEIS Clean Innovation sectors (Appendix 2 details how these sectors were derived) as well as on the "Trending" category, a collection of cutting edge fields that often receive particular attention in the public debate on innovation. Looking first at the right panel we see that the return on clean innovations – defined either by the BEIS definition or via the EPO definition – exceeds that of any other technology category including the trending category. That said: we see from the left panel that returns are very heterogenous within various subclasses of the clean and trending categories: we find that Tidal Stream and Offshore Wind technologies in particular lead to returns that are more than twice the average return across all categories. CCUS, Smart Systems and Building Fabric are further categories that are above average returns. Hydrogen is exactly at the average return, and ranks above all other clean categories considered. Note that the right panel also shows considerable heterogeneity for different trending technologies, although the highest return category (wireless) is still below the leading clean fields Tidal and Offshore.

The overall domestic UK return appears rather low. The average return for clean technologies as defined by BEIS is a mere 3.3%. However, as we discussed above, the IStraX measure will provide a robust indicator for the relative return across different technology categories. Its reliability to compute the absolute level of return is more limited. In addition, there are several factors that imply that it provides at best a lower bound, most importantly because knowledge spillovers take time to occur. Hence, the most recent innovations (in our dataset) will have had little opportunity to produce any spillovers irrespective of their actual ability to do so. In the appendix we explore this issue by reporting R&D returns (In Figure **11**) for different technology groups using only innovations for the period 2005-2009; i.e. innovations that had at least an interval of 5 years to accumulate spillovers. This analysis shows two interesting patterns: First, restricting to the earlier half of the time-window has no effect on the ranking of different technology groups, confirming our earlier suggestion that the ranking of technologies is robust. Second, we see a substantial increase in the reported rates of return. The average rate of return for the BEIS definition of clean technologies is now nearly 6%. This is still a lower bound because innovations from 2005-2009 are expected to generate spillovers after 2014. To examine the extent of spillover creation in the long run, **Figure 13** plots the average yearly spillovers generated by inventions from the year 1990. It shows that spillover creation is largest 7 years after the invention. Afterwards spillovers level off to about 1/3 the peak value, but remain rather stable until 2014, the end of the sample period. Cumulatively, about 50% of the total spillovers are realized within 8 years of the invention and 75% within 15 years. Taken together, these results suggest that the long-term benefits of R&D support are considerably larger than those estimated in this report but that ignoring those longer term spillovers has little impact on the ranking of technology fields.

Our return rates are estimated for innovative activity between 2005-2014. Whether these estimates are predictive for future subsidy return rates is hard to tell with certainty. However, we can analyse the extent to which they have been historically stable over time. **Figure 14** in Appendix 1 addresses this question. It compares UK national return rates for two intervals, 2000-2009 and 2005-2014, at the level of 128 CPC classes. The correlation between the two periods is 0.53. While this shows there is scope for improving predictive power, return rates seem to be reasonably stable over time. This provides suggestive evidence that the return rates we estimate are indicative of future returns to subsidies.

Figure 8: Within UK social returns to R&D subsidies in the UK by technological field



Notes: Expected returns to government R&D subsidies (IstraX) by technology field (y-axis) and 95% confidence bands. The (vertical) width of a bar indicates the size of a particular technology grouping by number of innovations. The x-axis shows the estimated returns within the UK to a £1 additional R&D subsidy in the field. Left-hand figure compares Clean innovation fields ('BEIS Clean Innovation Sectors' groups sectors as described in Appendix 2; 'Total UK Clean Innovation' uses the EPO 'Y02'-class to group patents into climate-change-mitigating technology) to other broad technology fields. Right-hand figure benchmarks particular Clean innovation subfields to a number of Trending subfields that have been identified as interesting subsidy targets. Dotted line represents the weighted average across technology fields.

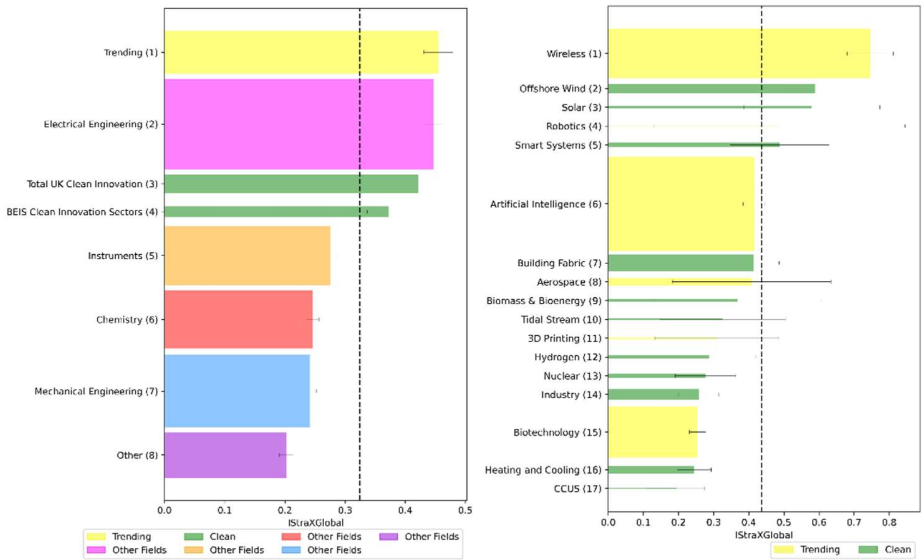
UK policy makers will be most keenly interested in spillovers that occur within the UK. Our methodology ensures that we pick up not only if such spillovers occur directly within the UK, but also if this occurs indirectly via other innovators that might not necessarily be UK based. However – as has been pointed out by Guillard et al (2021) – spillovers in relatively small and open economies mainly benefit inventors in different countries. Being such an economy, it is meaningful for the UK to also examine – next to within-UK returns – the global returns generated.

Figure **9** examines global social returns to R&D subsidies and reveals several points. First, we see dramatically higher rates of return; e.g. we find an average return rates of 35%-40% for clean technologies as a whole as opposed to 3.3% for national returns only. This confirms the gap found in Guillard et al. (2021) between within-country and global spillovers for countries in Europe. In part, this gap could be explained by the size of the UK economy relative to the size of the rest of the world. However, it could also reflect specific features of the UK economy, such as greater openness, a less strategic approach to industrial and innovation policy[13], or the UK being at the frontier of knowledge producing cutting edge technology with high value for technology development elsewhere. Second, in terms of global returns the ranking of

[13] For instance, Guillard et al (2021) show that a number of economies such as South Korea or Germany that are of comparable size to the UK have substantially higher rates of spillover internalisation; i.e. spillover flows within the respective countries as a share of total spillovers generated.

technologies is different. Clean technologies as a whole still show above average returns. However, as a group they are now eclipsed by both Trending and Electrical Engineering technologies. Also within clean technologies there is a shift in the relative ranking. While offshore wind and Smart Systems are still leading, Tidal Stream technologies are now on rank 10 whereas in particular solar technology has moved up.

Figure 9: Global social returns to R&D subsidies in the UK by technological field



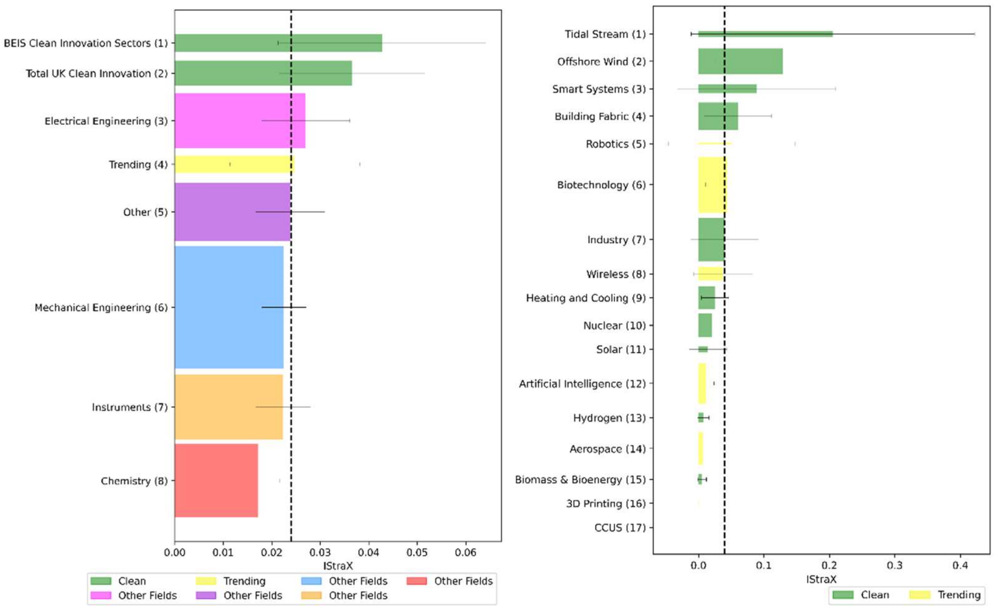
Notes: Expected returns to government R&D subsidies (IstraX) by technology field (y-axis) and 95% confidence bands. The (vertical) width of a bar indicates the size of a particular technology grouping by number of innovations. The x-axis shows the estimated global returns to a £1 additional R&D subsidy in the field. Left-hand figure compares Clean innovation fields ('BEIS Clean Innovation Sectors' groups sectors as described in Appendix 2; 'Total UK Clean Innovation' uses the EPO 'Y02'-class to group patents into climate-change-mitigating technology) to other broad technology fields. Right-hand figure benchmarks particular Clean innovation subfields to a number of Trending subfields that have been identified as interesting subsidy targets. Dotted line represents the weighted average across technology fields.

4.3 Technological readiness

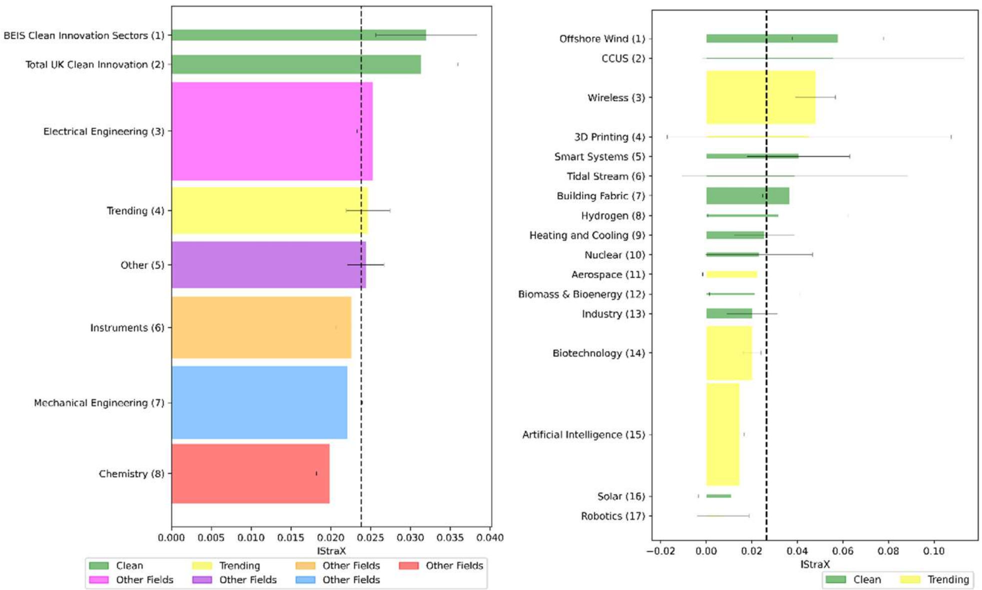
An important characteristic of an innovation project is its technological readiness (TRL). Should governments focus their funding efforts on projects that are more or less technologically ready? Part of the answer to this might depend on the degree to which TRL determines knowledge spillovers. TRL is not a characteristic that is recorded within patent documents. As a substitute, we use a measure of the (radical) novelty of an innovation. Hence, we consider a more radical project to be less technologically ready. Figure 10 shows within-UK social return figures (IStraX) separately for innovations with low (radical) and high (not radical) TRL. We see that rankings for the broadly-defined classes are very similar between TRL levels and equivalent to the overall results. In particular clean technologies show the highest levels of return. Also note that, in most cases, low TRL levels are associated with higher economic returns. However, this is not the case for all categories. For Chemistry and Instruments the ranking is reversed (see also Table 1). The ranking of the detailed clean and trending categories is also similar between low and high TRL levels. Although there are some notable exceptions: CCUS is creating more social value when it comes to high TRL whereas it ranks last in terms of low TRL.

Figure 10: Social returns (IStraX) within the UK by technological readiness

TRL Low



TRL High



Notes: Expected returns to government R&D subsidies (IstraX) by technology field (y-axis) and 95% confidence bands for innovations with low (upper panel) and high (lower panel) levels of TRL. The (vertical) width of a bar indicates the size of a particular technology grouping by number of innovations. The x-axis shows the estimated returns within the UK to a £1 additional R&D subsidy in the field. Left-hand figure compares Clean innovation fields (‘BEIS Clean Innovation Sectors’ groups sectors as described in Appendix 2; ‘Total UK Clean Innovation’ uses the EPO ‘Y02’-class to group patents into climate-change-mitigating technology) to other broad technology fields. Right-hand figure benchmarks particular Clean innovation subfields to a number of Trending subfields that have been identified as interesting subsidy targets. Dotted line represents the weighted average across technology fields.

Table 1: ISTRAX by technological readiness

	Share high TRL	IStraX low TRL	IStraX high TRL
Broad fields			
BEIS Clean Innovation Sectors	0.8822	**0.0428**	0.0320
Total UK Clean Innovation	0.9022	**0.0366**	0.0313
Chemistry	0.9059	0.0171	**0.0199**
Electrical Engineering	0.9552	**0.0270**	0.0252
Instruments	0.9187	0.0223	**0.0226**
Mechanical Engineering	0.8755	**0.0225**	0.0220
Trending	0.9695	0.0247	0.0247
Other	0.9061	0.0238	**0.0244**
Narrow fields			
3D Printing	0.7330	0.0004	**0.0452**
Aerospace	0.8118	0.0069	**0.0224**
Artificial Intelligence	0.9823	0.0119	**0.0145**
Biomass & Bioenergy	0.8371	0.0054	**0.0212**
Biotechnology	0.9554	**0.0434**	0.0200
Building Fabric	0.9313	**0.0602**	0.0365
CCUS	0.8430	0.0000	**0.0556**
Heating and Cooling	0.8791	0.0251	**0.0255**
Hydrogen	0.8462	0.0073	**0.0315**
Industry	0.8328	**0.0396**	0.0201
Nuclear	0.7834	0.0207	**0.0231**
Offshore Wind	0.8820	**0.1285**	0.0578
Robotics	0.8750	**0.0507**	0.0074
Smart Systems	0.9255	**0.0886**	0.0405
Solar	0.9071	**0.0143**	0.0110
Tidal Stream	0.8503	**0.2054**	0.0388
Wireless	0.9887	0.0374	**0.0479**

Notes: Summary of results from the TRL analysis. First column shows the share of innovations with high TRL by technology field. This share is equal to 1 minus the share of innovations that are classified as novel as measured by introducing new combinations of technology classes. Second and third columns compare the IStraX indicator for low- and high-TRL innovations respectively. Bold format indicates the maximum IStraX by TRL-level.

5. Conclusion

In this study we have examined a number of approaches to compute the social return of public R&D subsidies for different technology groups with a particular focus on various Clean technology types for the UK. Our most advanced approach – dubbed Industrial Strategy Index (ISTRAX) – takes into account both direct and indirect knowledge spillovers to compute economic return. We also account for the possibility that governments might struggle to only fund additional innovation. We also distinguish between innovation spillovers that are internalised within the UK and those that are not.

This leads to robust evidence that returns from clean technologies are substantially higher than returns from other technology groups including a set of trending technologies that are often discussed as cutting edge. However, there is considerable heterogeneity across various clean subgroups. That said: we find a surprisingly robust ranking across classes with Tidal Stream, Offshore wind, CCUS, Smart Systems and Building Fabric displaying the highest/above average returns and Solar, Biomass, Nuclear and Industry trailing the ranking – with solar coming lowest.

Hence, this suggest that prioritising the leading categories as part of the governments clean innovation portfolio would not only help to address the UK's net zero ambition but could also make a contribution towards economic growth.

References

Acemoglu, D., Hemous, D., Barrage, L., & Aghion, P. (2019). Climate Change, Directed Innovation, and Energy Transition: The Long-run Consequences of the Shale Gas Revolution. *2019 Meeting Papers*. https://ideas.repec.org/p/red/sed019/1302.html

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., & van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy*. https://doi.org/10.1086/684581

Alcacer, J., & Gittelman, M. (2006). Patent citations as a measure of knowledge flows: The influence of examiner citations. *The Review of Economics and Statistics*, 88(4), 774-779.

Arrow, K. J. (1962). Economic Welfare and the Allocation of Resources for Invention. In R. Nelson (Ed.), *The Rate and Direction of Inventive Activity*. Princeton University Press.

Baumann, M., Domnik, T., Haase, M., Wulf, C., Emmerich, P., Rösch, C., Zapp, P., Naegler, T. & Weil, M. (2021) Comparative patent analysis for the identification of global research trends for the case of battery storage, hydrogen and bioenergy. *Technological Forecasting and Social Change,* 165.

Bernstein, J. I. and Nadiri, M. I. (1989). Research and Development and Intra-industry Spillovers: An Empirical Application of Dynamic Duality. *The Review of Economic Studies*, 56(2):249.

Bloom, N., Schankerman, M., and Reenen, J. V. (2013). Identifying Technology Spillovers and Product Market Rivalry. *Econometrica*, 81(4):1347–1393.

Dechezleprêtre, A., Martin, R., & Mohnen, M. (2014). Knowledge Spillovers from Clean and Dirty Technologies. In *CEP Discussion Paper* (CEP Discussion Paper, Issue 1300).

Griliches, Z., (1986). Productivity, R&D, and the Basic Research at the Firm Level in the 1970's. *American Economic Review*, *76*(1), 141–154. https://econpapers.repec.org/RePEc:aea:aecrev:v:76:y:1986:i:1:p:141-54

Griliches, Z. (1991). The Search for R&D Spillovers. Technical report, National Bureau of Economic Research, Cambridge, MA.

Griliches, Z. (1992). The Search for R&D Spillovers. *The Scandinavian Journal of Economics*, *94*, S29. https://doi.org/10.2307/3440244

Guillard, C., Martin, R., Mohnen, P., Thomas, C., & Verhoeven, D. (2021). Efficient industrial policy: Standing on the shoulders of hidden giants. *CEP Discussion Paper No. 1813. https://cep.lse.ac.uk/_NEW/PUBLICATIONS/abstract.asp?index=8614*

Jaffe, A. B. (1986). Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value.The *American Economic Review*,76 (Feb. 1986):984–1001.

Jaffe, A. B., Trajtenberg, M., and Henderson, R. (1993). Geographic Localization ofKnowledge Spillovers as Evidenced by Patent Citations. *The Quarterly Journal of Economics*, 108(3):577–598.

Johnstone, N., Haščič, I.,& Popp, D. (2010) Renewable energy policies and technological innovation: evidence based on patent counts. *Environmental and Resource Economics,* 45, 133-155.

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics*, *132*(2), 665–712. https://doi.org/10.1093/qje/qjw040

Martin, R., Unsworth, S., Valero, A., & Verhoeven, D. (2020). *Innovation for a strong and sustainable recovery*. http://cep.lse.ac.uk

Noailly, J. (2012). Improving the energy efficiency of buildings: The impact of environmental policy on technological innovation," *Energy Economics,* 34(3), 795-806.

Page, L., Brin, S., Motwani, R., & Winograd, T. (1999). *The PageRank citation ranking: bringing order to the web.*

Popp, D., Pless, J., Haščič, I., & Johnstone, N. (2020). Innovation and Entrepreneurship in the Energy Sector. *NBER Working Paper*, *27145*. https://doi.org/10.3386/W27145

Renaldi, R., Miranda, N.D., Khosla, R., McCulloch, M.D. (2021). Patent landscape of not-in-kind active cooling technologies between 1998 and 2017. *Journal of Cleaner Production,* 296.

Rydge, J., Martin, R., & Valero, A. (2018). *Sustainable growth in the UK Seizing opportunities from technological change and the transition to a low-carbon economy.* CEP Industrial Strategy Paper 7 http://cep.lse.ac.uk/pubs/download/is07.pdf

Scherer, F. M. (1965). Firm Size, Market Structure, Opportunity, and the Output of Patented Inventions. Technical Report 5, American Economic Association.

Sharifzadeh, M., Triulzi, G., & Magee, C.L. (2019) Quantification of technological progress in greenhouse gas (GHG) capture and mitigation using patent data. *Energy & Environmental Science*, 12(8).

Trajtenberg, M. (1990). A Penny for Your Quotes: Patent Citations and the Value of Innovations. Technical Report 1.

Unsworth, S., Valero, A., Martin, R., & Verhoeven, D. (2020). *Seizing sustainable growth opportunities from zero emission passenger vehicles in the UK Special report for the Seizing sustainable growth opportunities from zero emission passenger vehicles in the UK*. CEP Special Report 37 http://cep.lse.ac.uk/pubs/download/special/cepsp37.pdf

Verhoeven, D., Bakker, J., & Veugelers, R. (2016). Measuring technological novelty with patent-based indicators. *Research Policy*, *45*(3). https://doi.org/10.1016/j.respol.2015.11.010

Vivid Economics. (2019). *Energy Innovation Needs Assessment*. Available at: https://www.gov.uk/government/publications/energy-innovation-needs-assessments

Appendix

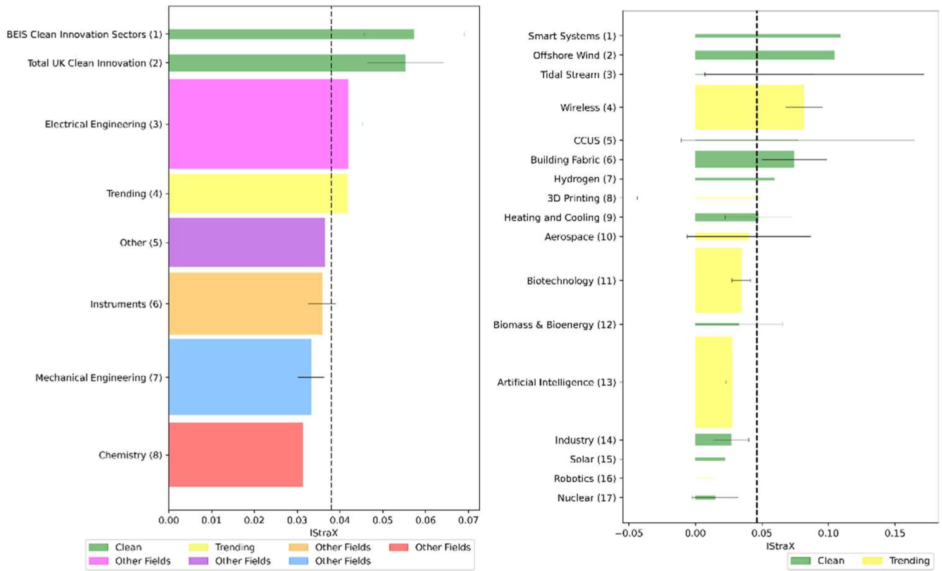
Appendix A: Additional Results

Robustness of IStraX calculations

In this section we provide a number of results to explore the robustness of our main results.

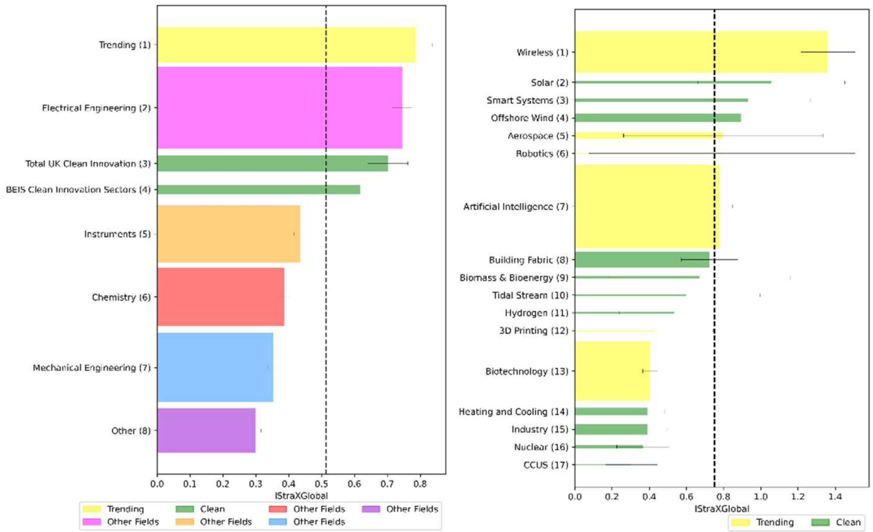
In Figure **11** and **12** public returns across technology categories restricting ourselves to 2005-2009 innovations only (rather than 2005-2014 innovations) while allowing for spillovers from innovations between 2005-2014 i.e. innovations that had at least an interval of 5 years to accumulate spillovers. This analysis shows two interesting patterns: First, restricting to the earlier half of the time-window has no effect on the ranking of different technology groups, confirming our earlier suggestion that the ranking of technologies is robust. Second, we see a substantial increase in the reported rates of return. The average rate of return for the BEIS definition of clean technologies is now nearly 6%. This is still a lower bound because innovations from 2005-2009 are expected to generate spillovers after 2014.

Figure 11: Within UK social returns to R&D subsidies in the UK by technological field (2005-2009 Innovations)



Notes: Expected returns to government R&D subsidies (IStraX) by technology field (y-axis) and 95% confidence bands. The innovations included are from the 2005-2009 period and we count spillovers induced by these innovation up to 2014. The (vertical) width of a bar indicates the size of a particular technology grouping by number of innovations. The x-axis shows the estimated returns within the UK to a £1 additional R&D subsidy in the field. Left-hand figure compares Clean innovation fields ('BEIS Clean Innovation Sectors' groups sectors as described in Appendix 2; 'Total UK Clean Innovation' uses the EPO 'Y02'-class to group patents into climate-change-mitigating technology) to other broad technology fields. Right-hand figure benchmarks particular Clean innovation subfields to a number of Trending subfields that have been identified as interesting subsidy targets. Dotted line represents the weighted average across technology fields.

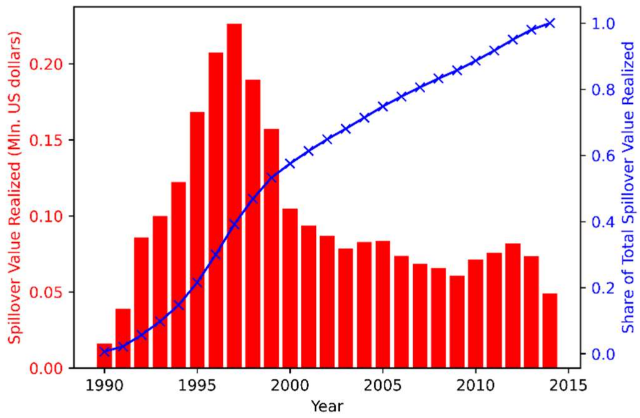
Figure 12: Global social returns to R&D subsidies in the UK by technological field (2005-2009 Innovations)



Notes: Expected returns to government R&D subsidies (IStraX) by technology field (y-axis) and 95% confidence bands. The innovations included are from the 2005-2009 period and we count spillovers induced by these innovation up to 2014. The (vertical) width of a bar indicates the size of a particular technology grouping by number of innovations. The x-axis shows the estimated global returns to a £1 additional R&D subsidy in the field. Left-hand figure compares Clean innovation fields ('BEIS Clean Innovation Sectors' groups sectors as described in Appendix 2; 'Total UK Clean Innovation' uses the EPO 'Y02'-class to group patents into climate-change-mitigating technology) to other broad technology fields. Right-hand figure benchmarks particular Clean innovation subfields to a number of Trending subfields that have been identified as interesting subsidy targets. Dotted line represents the weighted average across technology fields.

To examine the extent of spillover creation in the long run, **Figure 13** plots the average yearly spillovers generated by inventions from the year 1990. It shows that spillover creation is largest 7 years after the invention. Afterwards spillovers level off to about 1/3 the peak value, but remain rather stable until 2014, the end of the sample period. Cumulatively, about 50% of the total spillovers are realized within 8 years of the invention and 75% within 15 years. Taken together, these results suggest that the long-term benefits of R&D support are considerably larger than those estimated in this report but that ignoring those longer term spillovers has little impact on the ranking of technology fields.

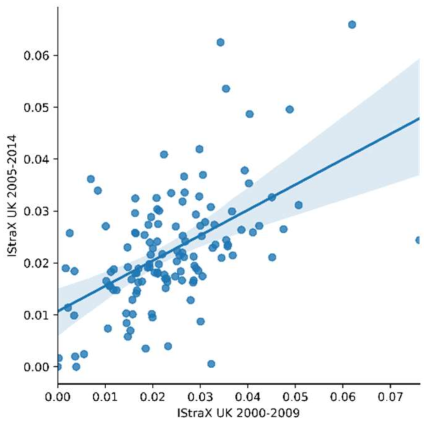
Figure 13: Global Spillovers Over Time



Notes: Analysis of spillovers generated by inventions from the year 1990. Bars (left y-axis) show the additional spillover value realized over time by the average 1990 innovation. Values are in 1982 US dollars and represent global spillovers. Line shows the cumulative fraction of spillovers realized over time. It shows how many of the total 1990-2014 spillovers were realized in a given year.

Our return rates are estimated for innovative activity between 2005-2014. Whether these estimates are predictive for future subsidy return rates is hard to tell with certainty. However, we can analyse the extent to which they have been historically stable over time. **Figure 14** addresses this question. It compares UK national return rates for two intervals, 2000-2009 and 2005-2014, at the level of 128 CPC classes. The correlation between the two periods is 0.53. While this shows there is scope for improving predictive power, return rates seem to be reasonably stable over time. This provides suggestive evidence that the return rates we estimate are indicative of future returns to subsidies.

Figure 14: Stability of IStraX over time



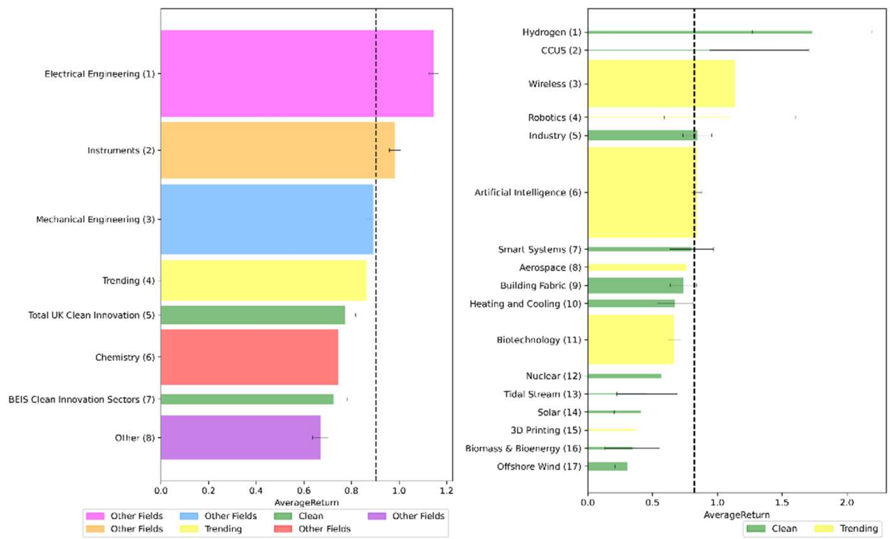
Notes: Analysis of the correlation between IStraX calculated for different time windows at the CPC Class level. For each of 128 CPC classes, we calculate IStraX UK national return rates for the periods 2000-2009 (x-axis) and 2005-2014 (y-axis). The blue line is the best linear fit and the shaded area is the confidence interval around this best fit estimated using bootstrapping with 1000 samples. The correlation coefficient between the two variables is 0.54, the Spearman rank correlation is 0.53.

Alternative measures of R&D subsidy return

Above, we focused on the marginal impact of R&D subsidies taking into account that such subsidies can only affect the overall amount of innovation by inducing firms to expand previously marginal projects. In other words, we assume that a large part of any extra public funding would simply provide a windfall gain for innovators within projects that would have gone ahead irrespective of the funding.

In this section, we show the results of using alternative indicators to rank technological fields, as suggested in the methods section. First, we calculate the average return on R&D investments (Equation 1) in projects that are undertaken in the absence of additional subsidies. Figure **15** shows the ranking of technological fields based on these overall returns to R&D investments. Two findings stand out. First, overall return rates to R&D investments are vastly higher as compared to the IStraX figures reported earlier. For instance, Clean technologies as classified by BEIS show returns of nearly 80%. This implies total economic returns from investing in R&D are very large. Second, rankings of technology fields differ substantially from rankings based on IStraX. Clean technologies as a whole are now ranked more towards the bottom. Also, within clean technologies, Tidal Stream and Offshore Wind – previously ranked first – are now in last and 5th to last place. However, some clean technologies – notably CCUS and hydrogen – are still ranked at or near the top of the ranking. Taken together, these findings suggest that designing R&D support programmes using overall returns realized with R&D that is undertaken regardless of additional R&D support, may be misleading. This approach assumes that R&D subsidies result in projects with equal private and spillover returns as those undertaken in the absence of government intervention. This is an unrealistic assumption because projects with substantial private benefits would likely have been undertaken already in the absence of any subsidy, and therefore are not induced by the subsidy itself.

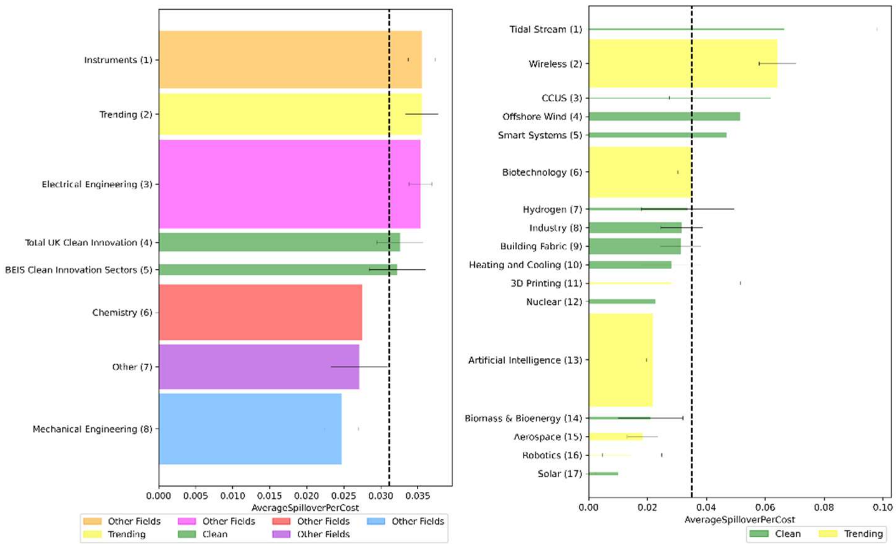
Figure 15: Average within UK returns per amount of R&D



Notes: Average returns to R&D (projects undertaken regardless of additional subsidies) by technology field (y-axis) and 95% confidence bands. The (vertical) width of a bar indicates the size of a particular technology grouping by number of innovations. The x-axis shows the sum of the private value and spillover value induced within the UK for an R&D investment of £1 in the field. Left-hand figure compares Clean innovation fields ('BEIS Clean Innovation Sectors' groups sectors as described in Appendix 2; 'Total UK Clean Innovation' uses the EPO 'Y02'-class to group patents into climate-change-mitigating technology) to other broad technology fields. Right-hand figure benchmarks particular Clean innovation subfields to a number of Trending subfields that have been identified as interesting subsidy targets. Dotted line represents the weighted average across technology fields.

Next, we construct rankings based on the average spillover value (EV) over R&D investment. This approach abstracts from any private returns that are generated from R&D investments. These return rates would reflect the returns to subsidies if we assume that R&D induced by subsidies do not increase the private returns of firms, but do generate spillover value (EV) equivalent to the average spillovers generated by R&D investments as observed in the absence of additional subsidies. As shown in **Figure 16**, using this indicator leads to returns to technology groups that are broadly in line with the findings for ISTRAX. These results indicate that private returns and spillover returns are not strongly correlated. Indeed, as IStraX assumes that the additional projects due to the subsidy are of lower private value, the absence of a strong correlation implies that the spillover value for these additional projects are not (much) lower. The fact that we observe similar returns is reassuring because it suggests that our baseline results are not driven completely by our assumptions on the (unobserved) value of projects below the private cost threshold.

Figure 16: Average within UK returns per amount of R&D – Spillovers only



Notes: Average spillover returns to R&D (projects undertaken regardless of additional subsidies) by technology field (y-axis) and 95% confidence bands. The (vertical) width of a bar indicates the size of a particular technology grouping by number of innovations. The x-axis shows the spillover value induced within the UK for an R&D investment of £1 in the field. Left-hand figure compares Clean innovation fields ('BEIS Clean Innovation Sectors' groups sectors as described in Appendix 2; 'Total UK Clean Innovation' uses the EPO 'Y02'-class to group patents into climate-change-mitigating technology) to other broad technology fields. Right-hand figure benchmarks particular Clean innovation subfields to a number of Trending subfields that have been identified as interesting subsidy targets. Dotted line represents the weighted average across technology fields.

Table 2: Comparison different indicators

	IStraX	IStraX Global	Average Returns (PV+EV-c)/c	Average Spillovers (EV-c)/c	Count
Broad fields					
BEIS Clean Innovation Sectors	0.0333	0.3719	0.7254	0.0322	6233
Total UK Clean Innovation	0.0318	0.4210	0.7742	0.0326	10676
Chemistry	0.0196	0.2463	0.7451	0.0275	32615
Electrical Engineering	0.0253	0.4466	1.1457	0.0354	51153
Instruments	0.0225	0.2754	0.9827	0.0355	33466
Mechanical Engineering	0.0221	0.2412	0.8918	0.0247	41084
Trending	0.0247	0.4549	0.8632	0.0355	24075
Other	0.0243	0.2021	0.6698	0.0271	25821
Narrow fields					
3D Printing	0.0332	0.3085	0.3750	0.0277	191
Aerospace	0.0195	0.4083	0.7610	0.0183	861
Artificial Intelligence	0.0145	0.4149	0.8404	0.0218	11316
Biomass & Bioenergy	0.0183	0.3681	0.3429	0.0210	313
Biotechnology	0.0211	0.2540	0.6680	0.0351	6161
Building Fabric	0.0383	0.4139	0.7377	0.0312	1966
CCUS	0.0466	0.1932	1.3234	0.0618	121
Heating and Cooling	0.0254	0.2445	0.6732	0.0281	935
Hydrogen	0.0278	0.2876	1.7323	0.0337	325
Industry	0.0236	0.2573	0.8458	0.0316	1286
Nuclear	0.0225	0.2763	0.5677	0.0227	531
Offshore Wind	0.0664	0.5891	0.3034	0.0515	1085
Robotics	0.0128	0.4877	1.0977	0.0147	80
Smart Systems	0.0441	0.4875	0.8006	0.0470	577
Solar	0.0113	0.5792	0.4085	0.0099	323
Tidal Stream	0.0669	0.3256	0.4579	0.0665	187
Wireless	0.0478	0.7456	1.1363	0.0642	5904

Notes: Summary table of different metrics by technology field. First column shows expected returns within the UK to government R&D subsidies (IStraX). Second column shows the global returns to government R&D subsidies (IStraX Global). Third and fourth columns show the average within-UK-returns to R&D and, respectively, the average within-UK-spillover-returns to R&D. Final column shows a count of the number of innovations in the field.

Appendix B: Patent Code Derivation

As part of this paper, BEIS developed a bespoke methodology to derive a set of patent codes relevant to the aforementioned 'BEIS Clean Innovation Sectors'. Here, we set out the methodology to note its strengths and weaknesses and provide a comprehensive list of patent code tables below.

To derive relevant codes, the approach was undertaken in four steps. First, an innovation framework was developed, centring around the findings detailed in the Energy Innovation Needs Assessment (henceforth referred as EINA) (Vivid Economics, 2019). These papers allow a bespoke set of search terms to be produced from innovation opportunities for the UK, creating a sufficiently granular – but bounded – set of patents that are relevant to BEIS' innovation programmes.14 Second, using the established framework, patents were searched using the CPC Espacenet Classification search tool, utilising the terms in the component breakdown and innovation opportunity descriptions. Third, EINA framework compliant patents were then sense-checked by engineers within the BEIS to obtain an estimate for the degree of relevancy that each patent code had in matching with the EINA framework.15 The general areas considered to have technological significance include (but not limited to) innovations in the following:

- Design, process efficiency, yield improvement.
- Cost reduction.
- Renewable energy, GHG reduction to achieve Net Zero.
- Technological reliability and sustainability.
- Health, safety, and risk reduction.
- Scalability and storage capacity.
- Energy from waste and its management.

The fourth step in this process was to further benchmark derived patent codes with existing academic studies. Published studies were selected which provided a list of patent codes for each sector, to ensure that core codes were not missing from the framework – the benchmark academic studies were not used as an exhaustive list, with the inclusion other codes conditional in relating to the underlying EINA framework.

The strength of this approach is foremost its relevance and applicability to BEIS innovation programmes. A result of this methodology ensures that core 'Y02' codes are included to provide a baseline set of patents, which are expanded upon into more granular technology areas of relevance. This approach generates a comprehensive set of codes to use, but also established consistency across BEIS-funded studies, resulting in well-aligned sectors of interest.

[14] Road Transport and Disruptive categories were not included due to falling outside BEIS' remit and difficulty in specifying relevant codes, respectively.
[15] This is noted in the below tables as the 'Engineering Relevance Rating'. Only those noted as 'High' and 'Medium' relevance were included.

The limitations of this approach derive from the subjectivity of which codes to include and those which are considered of engineering relevance. This could lead to bias with the inclusion and/or exclusion of various innovation categories. However, in an effort to counteract any bias, all codes have been closely aligned to a pre-existing innovation framework and benchmarked to existing academic studies. These robustness tests have demonstrated strong alignment that often goes above and beyond existing academic studies and methods to establish patent codes.

The patent derivation methodology also leads to substantial heterogeneity within the sector groupings. For example, the hydrogen classification covers a broad set of patents for production, distribution, and storage, whilst offshore wind is primarily focused on generation only. Consideration therefore needs to be applied to ensure conclusions are accurately made across technology classifications. Detailed insight to break down larger sectors may be an area to merit potential further research.

A further limitation to this approach stems from the bespoke alignment to UK innovation priorities at a single point in time. The changing dynamics of innovation – and subsequent innovation priorities – are likely to shift, meaning the alignment to future policy needs may diminish over time. Furthermore, the use of a UK-specific innovation needs framework restricts the ability of international comparisons when using the same patent sectors. A solution to this could be to consider the Global Innovation Needs Assessment (GINA) framework and innovation priorities to provide more universal coverage. 16

The below tables detail the patent codes derived for each BEIS Clean Innovation Sector. Core "Y02" codes have been highlighted in red, which represent a fundamental baseline for sector innovations.

[16] See: https://www.climateworks.org/report/ginas/

Table 3: Biomass & Bioenergy Patent Codes

Biomass & Bioenergy
Academic Benchmark: Johnstone (2010) Renewable energy policies and technological innovation: evidence based on patent counts.

Component		***Patent Codes***	**Engineering 'Relevance Rating'**	***Patent Code Description***
Component	Scale-up Deployment Link to CCUS Renewable hydrogen	**Y02E 50/00**	High	Technologies for the production of fuel of non-fossil origin Biofuels, e.g. bio-diesel; Fuel from waste, e.g. synthetic alcohol or diesel
Gasifier	Feedstock Gasifier Syngas cleanup	C10J2300/0916	High	Details of gasification process, Biomass
BioH2 and Bio-SNG	Water-Gas Shift (WGS) Reaction	C12M21/04	Medium	Bioreactors or fermenters for producing gas, e.g. biogas.
Fischer-Tropsch Synthesis	FT Catalyst FT reactor Upgrading	C10G2300/1022 C01B2203/062	High	Aspects relating to hydrocarbon processing covered by groups > Feedstock Materials > Fischer-Tropsch products Integrated processes for the production of hydrogen or synthesis gas (Hydrocarbon production e.g. Fischer-Tropsch process)
Syngas to Methanol	Overall Process	C01B2203/061	High	Integrated processes for the production of hydrogen or synthesis gas (Methanol production)
Woody & Grassy Energy Crops -SRC & Miscanthus	Breeding & Crop R&D Growing and harvesting, improving agronomics	A01C7/00 A01C 15/00 A01C 17/00 A01C 19/00 A01C 21/00 A01D45/30 A01H1/12 Y02A 40/10	Medium	Sowing Seeds Fertiliser Distribution Fertisliser or seeders with centrifugal wheels Arrangements for driving working parts of fertilisers or seeders Methods of fertilising Harvesting of standing crops (of grass-seeds or like seeds). Processes for modifying genotypes > Processes for modifying agronomic input traits, (e.g. crop yield, drought, cold, pest resistence)
Novel Oil Crops	Breeding & Crop R&D Growing and harvesting, improving agronomics	C11B1/00	High	Production of fats or fatty oils from raw materials (under head of vegitable oils).
Lignocellulosic feedstock pre-treatment & hydrolysis	Pre-treatment Hydrolysis	C12P2201/00 C08H8/00	High	Pretreatment of cellulosic or lignocellulosic material for subsequent enzymatic treatment or hydrolysis Macromolecular compounds derived from lignocellulosic materials
Lignocellulosic ethanol	Overall process	C12P7/10	High	Preparation of Ethanol substrate containing cellulosic material
Syngas fermentation	Pre-treatment Reactor Bacteria	C12M21/04 C10L3/08 C10L3/10	High	Bioreactors or fermenters specially adapted or producing gas, e.g. biogas Production of synthetic natural gas Working-up natural gas or synthetic natural gas
Feedstock Pre-treatment	Pre-treatment	C10G2300/10 Y02P20/145	Medium	Feedstock materials (covers: waste, vegetal biomass, animal biomass, natural gas, gas hydrates, hydrocarbon fractions, Fischer-Tropsch etc) Feedstock of biological origin
Digestion		C12M21/04	Medium	Bioreactors or fermenters specially adapted or producing gas, e.g. biogas

Table 4: Building Fabric Patent Codes

Building Fabric

Academic Benchmark: Noailly (2012). Improving the energy efficiency of buildings: The impact of environmental policy on technological innovation

Component		Patent Codes	Engineering 'Relevance Rating'	Patent Code Description
Pre-Construction and Design	New Build and Existing	Y02B10/00	High	Integration of renewable energy sources in buildings.
	New Build			
Materials and Components	New Build	F24S	High	Solar Heat Collectors
	(Some retrofits)	E06B3/24		Double Glazing
	New Build and Existing	E06B3/20		Vinyl wind frame
		E06B1/325		Thermal Break between Frames
		E04B1/74		Insulation materials
		E04B1/76		Heat insulation only
		E04F15/18		Floor Insulation
		E04D13/16		Roof Insulation
		F16L59/00		Thermal insulation of pipes
		F21Y2115/10		LEDs
Build Process	New Build and Existing	Y02B80/00	High	Architectural or constructional elements improving the thermal performance of buildings
Building Operation	New Build and Existing	Y02B90/00	High	Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation (Fuel cells in buildings & Smart Grids for buildings)
All	New Build and Existing	**Y02B**	High	climate change mitigation technologies related to buildings, e.g. housing, house appliances or related end-user applications

Table 5: Carbon Capture, Use & Storage patent codes

Carbon Capture, Use & Storage				
Academic Benchmark: Magee et al (2019) Quantification of technological progress in greenhouse gas (GHG) capture and mitigation using patent data				
Component		**Patent Codes**	**Engineering 'Relevance Rating '**	**Patent Code Description**
Power	Gas post-combustion capture	**Y02C20/00**	High	Capture or disposal of greenhouse gases
	Gas pre-combustion capture	B01D53/00		Separation of gases or vapours; Recovering vapours of volatile solvents from gases; Chemical or biological purification of waste gases, e.g. engine exhaust gases, smoke, fumes, flue gases, aerosols
	Gas Oxy-combustion capture	Y02E20/18	High	Integrated gasification combined cycle [IGCC], e.g. combined with carbon capture and storage [CCS]
	Solid fuel Post-combustion capture	Covered by Y02C20/00	High	
	Solid fuel Post-combustion capture	Covered by Y02C20/00	High	
	Solid fuel Pre-combustion capture	Covered by Y02C20/00	High	
	Solid fuel Oxy-combustion	Covered by Y02C20/00	Medium	
	CO_2 Storage: Infrastructure & injection wells	Y02P90/70	High	Combining sequestration of CO2 and exploitation of hydrocarbons by injecting CO2 or carbonated water in oil wells
Industry	Cement	Y02P40/18	High	Production of cement - Carbon capture and storage
	Chemicals	Y02P20/151	High	Technologies relating to chemical industry - Reduction of GHG emissions e.g. CO2
	Iron & steel	Y02P10/122	High	Technologies relating to metal processing - by capturing or storing CO2
	Refining	B01D53/00	Medium	Separation of gases or vapours; Recovering vapours of volatile solvents from gases; Chemical or biological purification of waste gases, e.g. engine exhaust gases, smoke, fumes, flue gases, aerosols,
	Cross-cutting	Y02P70/10	Medium	Final consumer goods - Greenhouse gas capture.

Table 6: Heating & Cooling Patent Codes

Component		Patent Codes	Engineering 'Relevance Rating'	Patent Code Description
Heating & Cooling				
Academic Benchmark: Renaldi (2021) et al. Patent landscape of not-in-kind active cooling technologies between 1998 and 2017				
Heat pumps	Heat source System Installation Integration O&M Installation	F25B30/00	High	Heat Pumps
Heat networks	Design Installation Connection to heat user Interface with heat user	**Y02B30/00** **Y02A30/27** C09K5/00	High	Energy efficient heating, ventilation or air conditioning [HVAC] Relating to heating, ventilation or air conditioning [HVAC] technologies Heat-transfer, heat-exchange or heat-storage materials, e.g. refrigerants; Materials for the production of heat or cold by chemical reactions other than by combustion
Heat storage	Heat source & sink	F24S	High	Solar Heat Collectors
	Heat store	**Y02E60/14** F24H7/00	High	Thermal energy storage Storage heaters, i.e. heaters in which energy is stored as heat in masses for subsequent release
Cooling	Main Unit System Design Control O&M Storage	F24F F25B	High	air-conditioning; air-humidification; ventilation; use of air currents for screening refrigeration machines, plants or systems; combined heating and refrigeration systems; heat-pump systems

Table 7: Hydrogen Patent Codes

Hydrogen

Academic Benchmark: Baumann et al. (2021) Comparative patent analysis for the identification of global research trends for the case of battery storage, hydrogen and bioenergy

Component		**Patent Codes**	**Engineering "Relevance Rating"**	**Patent Code Description**
Natural Gas Reforming	Integration with CCS Reformer Water-gas shift reactor Reformer	**Y02E60/30** C01B2203/02 C01B3/00	High	Hydrogen Technology, Storage & Distribution Processes for making hydrogen or synthesis gas (reforming & partial oxidation) Hydrogen; Gaseous mixtures containing hydrogen; Separation of hydrogen from mixtures containing it.
Coal Gassification	Integration with CCS Gasifier + Gas Purification Unit Gasifier Air Separation Unit (ASU)	C10J3/00	High	Production of combustible gases containing carbon monoxide from solid carbonaceous fuels
Electrolysis	Manufacturing Cell Cell Purification Equipment Purification Equipment System Integration Other Routes Other Applications Modelling	C25B1/02 Y02E60/36 (Covered by Y02E60/30) C25B11/00	High	Electrolytic production of inorganic compounds or non-metals > Hydrogen or oxygen > by electrolysis of water Hydrogen production from non-carbon containing sources, e.g. by water electrolysis Electrodes; Manufacture thereof not otherwise provided for
Delivery	Pressure Levels Safety Pipelines Tube Trailers Compression Liquefaction Process Alternative Carriers Odorants Sensors	F25J1/00 Y02E60/34 (covered by Y02E60/30) F17C5/02	High	Processes or apparatus for liquefying or solidifying gases or gaseous mixtures Hydrogen Distribution Methods or apparatus for filling containers with liquefied, solidified, or compressed gases under pressures > for filling with liquefied gases e.g. helium or hydrogen
Storage	Alternative Hydrogen Storage Alternative Hydrogen Storage Cavern Topside Facility Underground Storage	Y02E60/32 (Covered by Y02E60/30)	High	Hydrogen Storage
Refuelling Stations	Purification Unloading Equipment Verification Design Standardisation	C01B3/50	High	Separation of hydrogen or hydrogen containing gases from gaseous mixtures, e.g. purification
Fuel cells	Manufacturing Manufacturing SOFC SOFC PEMFC PEMFC Design Grid Services	H01M8/00 Y02E60/50 (Covered by Y02E60/30)	High	Fuel cells; Manufacture thereof Fuel cells

Table 8: Industrial Clean Innovation Patent Codes

<table>
<tr><td colspan="5">Industry</td></tr>
<tr><td colspan="5">Academic Benchmark: N/A</td></tr>
<tr><th colspan="2">Component</th><th>Patent Codes</th><th>Engineering ' Relevance Rating '</th><th>Patent Code Description</th></tr>
<tr><td rowspan="7">Chemicals</td><td>Efficiency improvements</td><td rowspan="7">Y02P20/00</td><td rowspan="7">High</td><td rowspan="7">Chemical Industry, includes:
- Process Efficiency
- Feedstocks
- Reduction of GHG emissions
- Energy Recovery
- Recycling catalysts/materials</td></tr>
<tr><td>Low-carbon substitutes</td></tr>
<tr><td>Heat recovery and reuse</td></tr>
<tr><td>Recovery and recycling</td></tr>
<tr><td>Energy systems</td></tr>
<tr><td>Alternative process technologies</td></tr>
<tr><td>Clustering</td></tr>
<tr><td rowspan="7">Food & drink</td><td>Efficiency improvements</td><td rowspan="7">Y02P80/00</td><td rowspan="7">High</td><td rowspan="7">Climate change mitigation technologies for sector-wide applications (note: not specific to food & Drink, but relevant for all sectors hence included)</td></tr>
<tr><td>Low-carbon substitutes</td></tr>
<tr><td>Heat recovery and reuse</td></tr>
<tr><td>Recovery and recycling</td></tr>
<tr><td>Energy systems</td></tr>
<tr><td>Alternative process technologies</td></tr>
<tr><td>Clustering</td></tr>
<tr><td rowspan="7">Iron & steel</td><td>Efficiency improvements</td><td rowspan="7">Y02P10/00</td><td rowspan="7">High</td><td rowspan="7">Technologies related to metal processing:

- Reduction in GHGs
- using alternative fuels
-using renewables
recycling
- process efficiency</td></tr>
<tr><td>Low-carbon substitutes</td></tr>
<tr><td>Heat recovery and reuse</td></tr>
<tr><td>Recovery and recycling</td></tr>
<tr><td>Energy systems</td></tr>
<tr><td>Alternative process technologies</td></tr>
<tr><td>Clustering</td></tr>
<tr><td rowspan="7">Cement</td><td>Efficiency improvements</td><td rowspan="7">Y02P40/10</td><td rowspan="7">High</td><td rowspan="7">Production of Cement:

- energy efficiency
- Fuels from renewables
- CCS
- Optimizing production methods</td></tr>
<tr><td>Low-carbon substitutes</td></tr>
<tr><td>Heat recovery and reuse</td></tr>
<tr><td>Recovery and recycling</td></tr>
<tr><td>Energy systems</td></tr>
<tr><td>Alternative process technologies</td></tr>
<tr><td>Clustering</td></tr>
<tr><td rowspan="5">Pulp & paper</td><td>Efficiency improvements</td><td rowspan="5">D21</td><td rowspan="5">Medium</td><td rowspan="5">paper-making; production of cellulose</td></tr>
<tr><td>Low-carbon substitutes</td></tr>
<tr><td>Heat recovery and reuse</td></tr>
<tr><td>Recovery and recycling</td></tr>
<tr><td>Energy systems</td></tr>
</table>

	Alternative process technologies Clustering			
Glass	Efficiency improvements Low-carbon substitutes Heat recovery and reuse Recovery and recycling Energy systems Alternative process technologies Clustering	**Y02P40/50**	High	Glass production, e.g. reusing waste heat during processing or shaping; improving yield and rejection rates
Ceramics	Efficiency improvements Low-carbon substitutes Heat recovery and reuse Recovery and recycling Energy systems Alternative process technologies Clustering	**Y02P40/60**	High	Production of ceramic materials or ceramic elements, e.g. substitution of clay or shale by alternative raw materials, e.g. ashes

Table 9: Nuclear Fission Patent Codes

Nuclear Energy			
Academic Benchmark: N/A			
Component	**Patent Codes**	**Engineering 'Relevance Rating'**	**Patent Code Description**
Mining, Processing, Enriching, Fabricating	**Y02E30/00** All of G21 (excluding G21J Nuclear Explosives)	High	Energy Generation of Nuclear Origin NUCLEAR PHYSICS; NUCLEAR ENGINEERING
CAPEX – Components and systems	Covered by G21 B33Y	High	Additive manufacturing technology
CAPEX – Construction and materials	Covered by G21	High	
CAPEX – Construction installation and commissioning	Covered by G21	Medium	
Operations and Maintenance	Covered by G21	Medium	
Decommissioning	Covered by G21	Medium	
Waste Management	Covered by G21	High	
Regulatory	Covered by G21	Medium	

Table 10: Offshore Wind Patent Codes

Offshore Wind				
Academic Benchmark: Johnstone (2010) Renewable energy policies and technological innovation: evidence based on patent counts				
Component		**Patent Codes**	**Engineering 'Relevance Rating'**	**Patent Code Description**
Floating wind:	Moorings	B63B 21/00	High	Tying-up; Shifting, towing, or pushing equipment; Anchoring
	Floating Foundations	B63B 2035/446	High	Floating structures carrying electric power plants for converting wind energy into electric energy
	Dynamic Cables	H01B7/12 H01B7/045	High	Floating cables, Flexible cables, conductors, or cords, e.g. trailing cables attached to marine objects e.g. buoys, diving equipment, aquatic probes, marine towline
Turbines		**Y02E10/70** F03D F05B 2240/21	High	Energy generation through renewable Energy sources (wind), Wind motors, control and rotation axis…etc, Components for wind turbines
Foundations	Foundation Optimisation	E02D27/00	High	Foundations as substructures
	New Foundation Design	E02D27/425		
Advanced Wind Modelling		G06F 30/00	Medium	Computer Aided Design

Balance of Plant (Transmission)	Longer Distance Transmission Grid Integration Grid Layout Array Cables HVDC Substations Substation Co-location	Y04S10/00 Y02E60/60 H02J 3/36 H02J 2003/365 H02J 13/00034	Medium	System supporting electrical power generation, transmission or distribution, Arrangements for transfer of electric power between AC networks or generators via a high voltage DC link (HVDC), Arrangements for transfer of electric power between ac networks via a high-tension dc link, Equipment being or involving an electric power substation
Operations & Maintenance	Remote Access Remote O&M O&M Optimisation	F03D 17 Y02P 80/00 H02J 13/365 G05B 13/00	High	Monitoring or testing of wind motors, e.g. diagnostics, Climate change mitigation technologies for sector-wide applications, Adaptive control systems, systems automatically adjusting themselves to have a performance which is optimum according to some preassigned criterion.
Installation (and logistics)	Advanced Lifting Innovative Installation Techniques Assembly	F03D 9/00 B63B 2035 E03D 27	High	Vessels or similar floating structures specially adapted for specific purposes and not otherwise provided, Wind motors specially adapted for installation in particular locations.
Energy storage	Offshore Wind Energy Storage Alternative Energy Storage	Y02E 70/30 F03D 9/10	Medium	Systems combining energy storage with energy generation of non-fossil origin.
Decommissioning & End of Life	Decommissioning Repowering Life Extension	F05B 2240	Medium	Component

Table 11: Smart Systems Patent Codes

Smart Systems				
Academic Benchmark: N/A				
Component		**Patent Codes**	**Engineering 'Relevance Rating '**	**Patent Code Description**
Smarter markets	Market platforms and aggregation	Y04S50/00	High	Market activities related to the operation of systems integrating technologies related to power network operation and communication or information technologies
		Y04S		systems integrating technologies related to power network operation, communication or information technologies for improving the electrical power generation, transmission, distribution, management or usage, i.e. smart grids
Demand side response	DSR – Homes/ buildings	covered by Y04S	High	
	DSR – EV integration	covered by Y04S	High	

Electricity storage	Bulk storage	Y04S10/14 Y02E70/30	High	Energy Storage Units Systems combining energy storage with energy generation of non-fossil origin
	Distributed storage	Y02E60/10	High	Energy Storage Using Batteries
	Distributed storage	Y02E60/16	High	Mechanical energy storage, e.g. flywheels or pressurised fluids
	Fast response storage	Y02E60/13	High	Energy storage using capacitors
Vector coupling	Power-to-gas	C25B1/02 Y02E60/36 C01C1/00	Medium	Electrolytic production of inorganic compounds or non-metals > Hydrogen or oxygen > by electrolysis of water Hydrogen production from non-carbon containing sources, e.g. by water electrolysis Ammonia; Compounds thereof
Networks	Networks	H02H9/00 Y02E40/00	High	Emergency protective circuit arrangements for limiting excess current or voltage without disconnection Technologies for an efficient electrical power generation, transmission or distribution
	Applications of HPC, AI and ML in data-rich energy systems	G06F30/27 G06F21/00	Medium	using machine learning, e.g. artificial intelligence, neural networks, support vector machines [SVM] or training a model Security arrangements for protecting computers, components thereof, programs or data against unauthorised activity

Table 12: Solar Patent Codes

Solar		
Academic Benchmark: Johnstone (2010) Renewable energy policies and technological innovation: evidence based on patent counts		
Patent Codes	**Engineering 'Relevance Rating'**	**Patent Code Description**
Y02E10/50	High	Photovoltaic [PV] energy
H01L31/00	High	Semiconductor devices sensitive to infra-red radiation, light, electromagnetic radiation of shorter wavelength or corpuscular radiation and specially adapted either for the conversion of the energy of such radiation into electrical energy or for the control of electrical energy by such radiation; Processes or apparatus specially adapted for the manufacture or treatment thereof or of parts thereof

H02S	High	Generation of electric power by conversion of infra-red radiation, visible light or ultraviolet light, e.g. using photovoltaic [pv] modules
F24S	High	Solar Heat Collectors
F03G6/00	High	Devices for producing mechanical power from solar energy

Note: Solar has been derived manually in the absence of an EINA framework specific to solar. All remaining steps have been the same

Table 13: Tidal Stream Patents

Tidal Stream			
Academic Benchmark: Johnstone (2010) Renewable energy policies and technological innovation: evidence based on patent counts.			
Component	**Patent Codes**	**Engineering 'Relevance Rating'**	**Patent Code Description**
Structure & Prime Mover	Y02E10/20 **Y02E10/30** F03B3/00	High	Hydro energy Energy from the sea, e.g. using wave energy or salinity gradient machines or engines for liquids
Power Take Off & Control	F03B15/00 E02B9/08	High	Controlling Machines or Engines for Liquids Tide or wave power plants
Foundations & Moorings	B63B2035/4466 E02D27/52 B63B21/00	High	Floating Structures carrying electric power plants (for converting water energy into electrical energy). Submerged foundations Tying-up; Shifting, towing, or pushing equipment; Anchoring
Connection	H01B7/12 H01B7/045	Medium	Floating cables, Flexible cables, conductors, or cords, e.g. trailing cables attached to marine objectis e.g. buoys, diving equipment, aquatic probes, marine towline

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